

CPAT Documentation

CPAT Team

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Cover



Foreword

Why CPAT?

The world faces the interconnected challenges of accelerating development and poverty reduction while addressing the climate challenge. Current policies, including climate commitments are not yet aligned with the Paris Agreement’s goal to hold “the increase in the global average temperature to well below 2°C above pre-industrial levels” and pursue efforts “to limit the temperature increase to 1.5°C above pre-industrial levels”. Much more action will be needed, despite a backdrop of multiple crises, slow growth, high debt and limited fiscal space. To meet these temperature levels, global greenhouse gas emissions must be cut by 21 to 43 percent by 2030 compared to 2019 (IPCC, AR6, Summary for Policymakers). Such an unprecedented rate of decarbonization necessitates climate mitigation policies across countries, notably carbon pricing, fossil fuel subsidy reform, renewable subsidies, feebates, emission rate regulations,

and public investments. To design and implement effective, efficient, and equitable policies governments need tools to assess economic, environmental, fiscal, and social impacts. To support this effort, the IMF and World Bank are making their joint Climate Policy Assessment Tool (CPAT) available to governments.

Among the proposed climate policies in the tool, carbon pricing offers an opportunity for countries to enhance their mobilization of domestic resources and improve the efficiency of the tax system, while creating an incentive for all economic actors – firms, investors, and households – to reduce their carbon emissions and favor greener technologies and behaviors. Combined with appropriate regulations and investments, carbon pricing is a key policy for countries to align their development and climate objectives. In particular, carbon pricing can offer a more efficient option to raise much-needed tax revenues, and generate short-term economic benefits through less distortive tax systems or enhanced investment in government services and infrastructure. It also provides financial resources that can be deployed to protect the poor and vulnerable populations against negative implications and avoid regressive impacts. Other development benefits include improvements in human health due to the co-emission of carbon emissions and local pollutants, and reductions in congestion and traffic-related accidents, for example as a result of a modal shift from private vehicles to public transit or soft modes.

What is CPAT

The Climate Policy Assessment Tool (CPAT) was developed to help countries provide a rapid evaluation of the potential impacts of climate policy reforms. As a global tool covering more than 180 countries, CPAT can be used as a one-stop-shop by anyone who is interested in a quick diagnostic of the potential benefits of a carbon price reform across multiple key dimensions, including not only emissions reduction potential and macroeconomic aggregates but also air pollution and health, road fatalities and congestion, and distributional impacts. It allows for the rapid quantification of impacts of climate mitigation policies, including on energy demand, prices, emissions, revenues, welfare, GDP, households and industries, local air pollution and health, and many other metrics. This documentation describes the CPAT model, its data sources, key assumptions, and caveats.

Why 400 pages of documentation?

CPAT is comprised of several economic models. Economic models describe a simplified reality and so they are, by definition, subject to considerable uncertainty. When interpreting the results of a model, knowing the underlying assumptions is critical. For this reason, several steps have been taken to improve the transparency of CPAT. First, the tool is spreadsheet-based with data and formulas readily accessible within the tool. Second, the tool is accompanied by a detailed 400-page documentation of the methodology which includes important caveats and cautions related to interpretation and data issues.

CPAT is designed to be a global public good. In a constantly evolving world, the tool will need continuous updating and upgrading. By putting together and releasing the detailed CPAT methodology, it is our hope that any interested party can adapt the tool for their own needs and contribute to its further development.

1 User Guide and Climate Policies in CPAT

This document provides guidance to the user on how to use and navigate CPAT and details the various climate policies available. In particular, Section 1.1 presents the different climate policies in CPAT. Section offers a quick start guide of CPAT in which the user can rapidly assess a climate policy via the dashboard. Section 1.2 presents the quick start guide of CPAT. For more in-depth understanding and use of CPAT and the different modules, Section 1.3 describes the different tabs including the dashboard of the CPAT tool and how to navigate through them. It also presents the Multiscenario Tool, which can be used to run CPAT for several countries and/or several scenarios. Section 1.4 provides CPAT's countries coverage. Finally, Section 1.5 presents the list of parameters of CPAT.

1.1 What climate policies can be assessed using CPAT?

1.1.1 Carbon Pricing Policies

The table below summarizes the climate policies options available in CPAT. The first column displayed the number corresponding to the policy in CPAT Excel-sheet. The carbon tax, ETS, feebate and energy efficiency regulations are qualified general policies as they cover all sectors. Nevertheless, exemptions can be applied for individual fuels and sectors (with the option to phase out exemptions over time). Other policies are sector- or fuel-specific.

	Policy	
Number	coverage	Description
1	Baseline	No climate policy implemented, except from those already captured by the prices data (e.g. existing ETS or carbon tax).
General policies		
2	Carbon tax	This policy represents a carbon tax applied to the supply of all fossil fuels in proportion to their carbon content. It is modeled by adding to the pre-existing tax on a particular fuel a charge equal to the product of the CO2 emissions factor for that fuel and the tax rate on CO2.

	Policy	
Number	coverage	Description
3	ETS	These policies are modeled in a similar way to a tax (CPAT is deterministic and does not capture uncertainty over emissions prices associated with ETSs). That is, CPAT requires the user to estimate the likely price of an ETS and then impose that to find the emissions reduction. ¹
4	Feebates	Feebates provide a revenue-neutral, sliding scale of fees on activities (like power generation) or products (like vehicles). Activities or products with above average emission rates pay a net tax; activities or products with below average emission rates get net revenues.
5	Energy efficiency regulations	These policies reduce the emissions or energy intensity of a sector but without the same demand response (e.g., reductions in VKT) as under carbon pricing because they do not involve the pass through of carbon tax revenues (or allowance rents) in higher prices (e.g., for electricity or gasoline) – they also produce a partially offsetting increase in emissions through the rebound effect.
Fuel or sector-specific policies		
6	Coal excise	The coal excise tax is a carbon tax (in the sense of it being defined per ton CO ₂) only on coal.
7	Road fuel tax	Taxes imposed on all fuels in the road transport sector.
8	Electricity emissions tax	This policy imposes a carbon tax on the electricity sector.
9	Power fee-bate	This policy covers power supply feebates if the engineer model is selected and covers power usage feebates if the elasticity model is selected.
10	Electricity excise	This policy translates into a tax per kWh of electricity used. The tax is set via the standard carbon tax interface. The tax in \$/tCO ₂ is mapped to one per kWh using the year one emission factor as a conversion factor.

¹A ‘goal seek’ functionality is set up in the dashboard (see Section 1.3.2.4 for more information) and allows the user to change the price in order to meet a particular emissions target in 2030.

Policy Number	Policy coverage	Description
11	Vehicle fuel economy	This imposes shadow prices (similar to a feebate) in the vehicle sector.
12	Residential efficiency regulations	Similar to the energy efficiency regulations, but it only applies to the residential sector.
13	Industrial efficiency regulations	Similar to the energy efficiency regulations, but it only applies to the industrial sector.

1.1.2 Fossil Fuel Subsidy Reform Policies.

In addition to these policies, CPAT allows the user to phase out fossil fuel subsidies and reform regulated prices. See the relevant sections below.

1.1.3 Power Sector Policies

The power sector model contains policies that adjust the cost of capital, adjust Power Purchase Agreements etc. See the relevant sections below.

1.2 Quick Start Guide: Climate Policy Assessment Tool (CPAT)

Welcome to CPAT! This guide aims to show you how to use CPAT, give you an idea of some common issues, and indicate CPAT's data needs.

What is CPAT? CPAT is a tool for analyzing the impacts of carbon pricing and fossil fuel reforms along several economic and non-economic dimensions.

Opening CPAT: CPAT is a spreadsheet-based tool. You need Excel 2016 or later. Since CPAT is a relatively large spreadsheet, please close other apps. Please ensure 'Automatic Calculations' are turned **on** (File > Options > Formulas).

Navigating CPAT: Please, navigate first to the **Dashboard** tab.

Excel Options

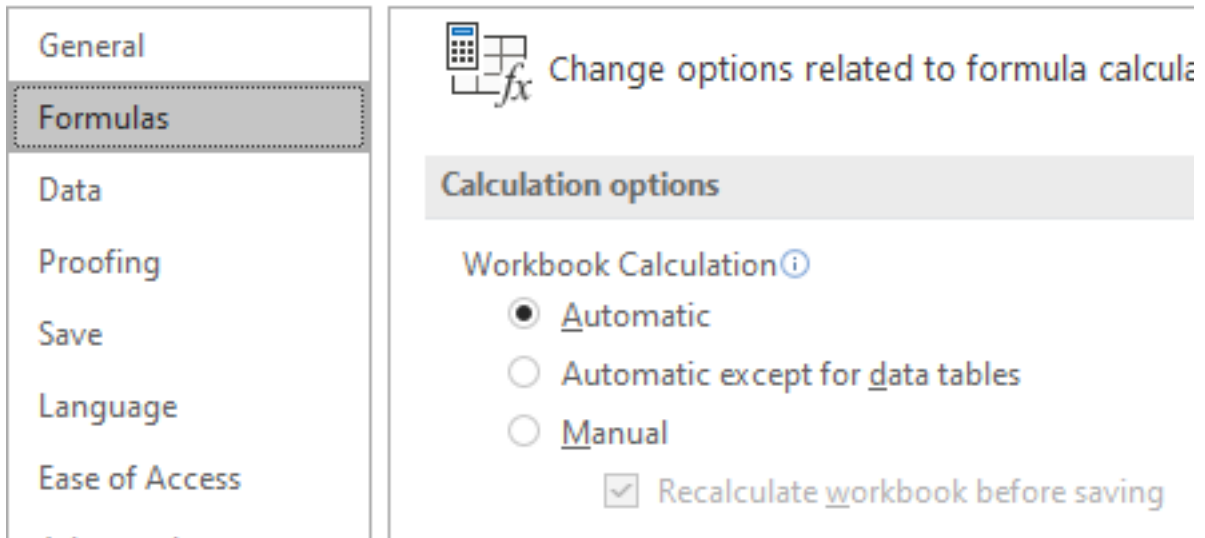


Figure 1.1: Automatic calculations

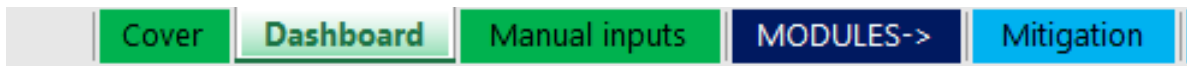


Figure 1.2: Navigation CPAT

1.2.1 Input: Country and Proposed Policy Trajectory

Policy Input Area: At the top left, you see various input cells. The yellow cells are user-editable. Categorical cells can be altered by clicking the small down arrow. By clicking on the cell which currently shows Carbon tax, you can select a different carbon pricing policy (e.g., an ETS), which comes with sectoral exemptions pre-set. All policies are defined by the carbon price. The carbon price trajectory is defined by the introduction date (here 2022), the start level (here \$50/tCO₂), the target level of the carbon price (here \$75/tCO₂), and the year that this target level will be met (here 2030).

	B	C	D	E	F	G	H	I
2		1 Select country -->	Poland					
3		2 Select policy -->	Carbon tax					
4		3 Define policy -->	Year to introduce new policy					2022
5			Starting carbon price (real USD per ton CO ₂)					50.0
6			Target level of carbon price					75.0
7			Year to reach target level					2030

Figure 1.3: Country and policy input area

Carbon Price Trajectory: To check that your suggested carbon tax is in place, please see the policy strength graph under *Key inputs and outputs*. On default settings, the policy is extended linearly beyond the end date. The dotted lines in the left-hand graph show the recommended range for a carbon price recommended by the High-level Commission on Carbon Pricing. The right-hand graph shows the policy's coverage, including any exemptions (see later for defining exemptions)

1.2.2 Output: Emissions, Revenues, and Co-Benefits

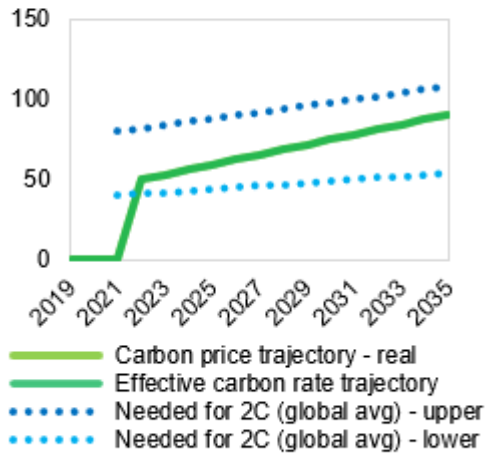
The main outputs are shown under *Key inputs and outputs* in *Panel B*. From the left, these graphs show:

1. GHG emissions relative to baseline (dashed line) & NDC target (dotted horizontal line)
2. Fiscal revenues (before recycling of funds)
3. Impact on projected GDP growth
4. Impacts on households (note: only countries for which household data are available)
5. Co-benefits: averted air pollution & road accident deaths
6. Total monetized benefits from the policy

Key inputs and outputs

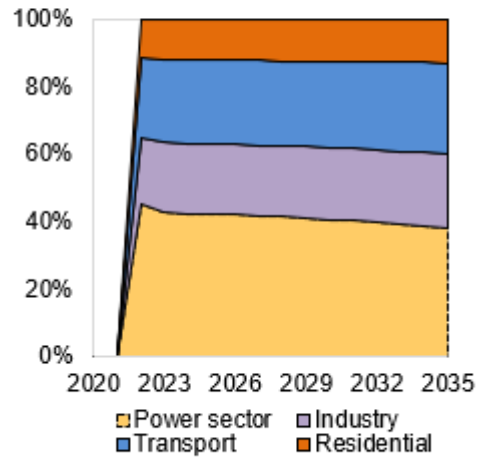
A Main policy design & macro drivers:

Policy strength: carbon price trajectory (US\$ per tCO₂e, 2018-2030), Poland



Effective carbon rate adjusts for coverage. Policy assumed to rise linearly after 2030.

Policy coverage: CO₂ emissions covered (% of national total)



Residual includes untaxed sectors e.g. military.

Figure 1.4: Carbon price trajectory

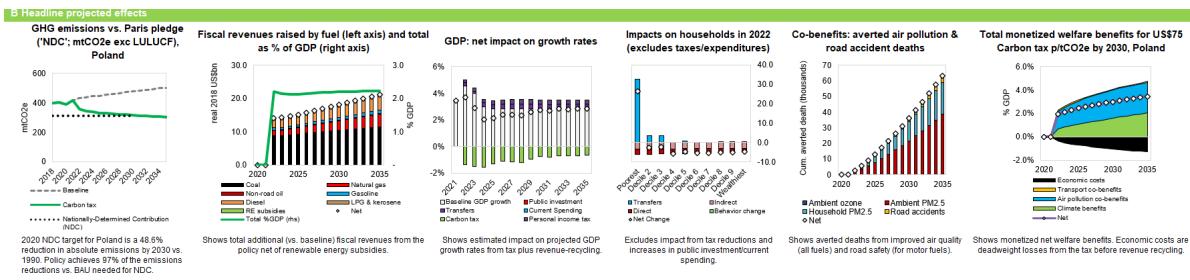


Figure 1.5: Key inputs and outputs

1.2.3 Sense-Checking

The CPAT team is constantly working to keep CPAT up to date, but CPAT is not bulletproof. You should run a few sense-checks as described below. Some of these checks relate to the reliability of input data. Many CPAT users can access national data sources. For continuous improvement of the tool, we would very much appreciate it if such data sources could be shared with us in case data is either missing or substantively different from what is currently in CPAT.

Check 1: Start by ensuring that the graphs show and update when you change carbon price inputs (i.e., there should be no errors in panel B: all graphs should show except, for some countries, the fourth graph on the impact on households).

Defaults for parameters: Click the + button for advanced settings.



Figure 1.6: The '+' button

This expandable panel contains a wide range of parameter settings and adjustments.

Default parameters are indicated with an asterisk (e.g., 'Base*'). Suppose you change a parameter away from its default setting. In that case, the color changes from yellow to orange. An indicator at the bottom of the 'Miscellaneous' section indicates the number of parameters that have departed from default values.

Check 2: Check how many defaults are different from expected. For default use, the line at the bottom of the Miscellaneous row should be blank/invisible.

Example of all settings set to default values

Miscellaneous:	
Include endogenous GDP effects?	Yes*
Residential LPG/kerosene always exempted	No*
National social cost of carbon (SCC) source	Target*
Congestion & road damage attributable to fuels	1%
Add non-climate Pigouvian tax on top?	No*
Years to phase-in non-climate Pigouvian tax?	5
Add additional excise tax (see 'Manual inputs' tab)?	No*
= default recommended	

Example of two settings NOT set to default values

Miscellaneous:	
Include endogenous GDP effects?	No
Residential LPG/kerosene always exempted	No*
National social cost of carbon (SCC) source	Target*
Congestion & road damage attributable to fuels	1%
Add non-climate Pigouvian tax on top?	Yes
Years to phase-in non-climate Pigouvian tax?	5
Add additional excise tax (see 'Manual inputs' tab)?	No*
# non-default parameter: 2 = default recommended	

1.2.4 Exemptions

One can exempt any fuels and sectors from the carbon tax (if unticked). So, if, e.g., Kerosene and Cement are unticked, all Kerosene is exempted (independent of the sector), and all Cement energy use is exempt (independent of fuel).

Check 3: Ensure that all checkboxes are ticked for full policy coverage (recommended) or unticked as desired.

4 Carbon tax policy coverage (other policies have predefined coverage):

Fuels: Coal Natural gas Gasoline Diesel LPG Kerosene Other oil products
Sectors: Power Road Rail Domestic aviation Domestic shipping Residential Other energy use
Industries: Food & forestry Services (private & public) Mining & chemicals Iron & steel Other metals
 Machinery Cement Other manufacturing Construction Fuel transformation & transportation

1.2.5 Phase-out exemptions, subsidies, and revenue recycling

On the right-hand side at the top of the dashboard, the user can change settings relating to the phase-out of exemptions, price controls, and subsidies. It also includes supplementing the policy with renewable energy subsidies and the use of revenues. For revenue recycling, there are five options: labor tax reductions, corporate tax reductions, public investment, current spending, and compensatory transfers to households.

6 Exemptions (fuels/sectors) -->	<input checked="" type="checkbox"/> Phaseout, starting in:	2022	5	years
7 Fossil fuel subsidies (producer) -->	<input checked="" type="checkbox"/> Phaseout, starting in:	2022	5	to
8 Fossil fuel subsidies (consumer) -->	<input checked="" type="checkbox"/> Phaseout, starting in:	2022	5	phase
9 Price controls (for fuels) -->	<input checked="" type="checkbox"/> Phaseout, starting in:	2022	5	out (if
10 Renewable subsidy -->	<input checked="" type="checkbox"/> Phaseout, starting in:	2022	5	applicable)
11 Revenue recycling -->	\$/kwh feed-in subsidy	\$ -	5	
	Labor tax reductions	50		% revenues used to reduce labor taxes (SSC, PIT)
	Corporate tax reductions	0		% revenues used to reduce corporate income (CIT)
	Public investment	50		% on e.g. public transport, infrastructure
	Current spending	0		% on e.g. health, education, social security
	Transfers:	0		% on transfer mechanisms (new lump-sum cash transfers)
	of which:	- targeted percentile	70	% from bottom of income distribution targeted for transfers
		- coverage rate	100	% of targeted percentile that receive transfers
		- leakage rate	0	% of untargeted percentile that receive transfers

Figure 1.7: Phase-out exemptions, subsidies, and revenue recycling

Check 4: The phase-out of exemptions, price controls, and subsidies, as well as the use of revenue, should be as desired by the user.

1.2.6 NDC data

CPAT includes data on countries' Nationally Determined Contributions (NDCs) under the UNFCCC. The 'NDCs' Tab summarizes the NDC baseline data for your country. As countries may be updating their NDCs, please check online in the [UNFCCC NDC Registry](#) if the information shown is up to date, and in line with the latest submitted version. If not, please, copy the table, fill it out, and send to the team.

Mitigation data - Nationally-Determined Contributions (NDCs) data			
Source: various			
NDC characteristics for Poland			National energy sector targets (from NDC)
NDC Type	Historical		Energy efficiency no targets
Reference year (for "Historical" and "Inter")	1990		
Conditionality apply	No		General energy no targets
Includes or excludes LULUCF?	Includes		
Target Year to Meet NDC	2030		
% Reduction in CO2 emissions relative to reference year			Renewable energy no targets
unconditional, economy-wide	-49%		
conditional, economy-wide	N/A		Clean cooking & heating no targets
Gases covered	PFCs, SF6, NF3		
NDC submission	2020 NDC		Gas & gas flaring no targets

Figure 1.8: NDC data

Check 5: Verify that NDC data are up to date.

1.2.7 Prices

Panel A under the *Mitigation module (macro & energy effects)* includes a table showing average fuel prices and tax-induced percentage changes. Price changes depend on carbon content as well as pre-existing price distortions (e.g., subsidies).

Note that a significant increase in the price of coal is expected in many countries, even under a moderate carbon tax. For example, \$80/t carbon tax with a coal emission factor at ~0.1 tCO₂/GJ would correspond to \$8/GJ carbon tax. If baseline (subsidized) coal prices were \$2/GJ with the subsidy around \$0.5/GJ, prices would increase 400%, even without subsidies phase-out. A more moderate situation is shown in the table to the right for Poland, where we see the price of coal increase by 164.8%.

Prices data quality: Look at [the heat map](#) to check the quality of the underlying price data. Information is color-coded (see the legend and suggested actions in the map): green shades mean reliable data sources, and yellow/orange cells mean that the users will have to check and confirm prices data.

Prices data form: if the user believes they have better prices data, they can choose to use 'manual' prices in calculations and fill the 'manual inputs' tab in CPAT. Also we recommend

Energy price changes for \$75/tCO₂ in 2030 (weighted by consumption)

Fuel	Unit	Baseline	Carbon tax	% change
Gasoline	US\$ per liter	1.09	1.27	17.2%
Diesel	US\$ per liter	1.12	1.34	19.5%
LPG	US\$ per liter	0.60	0.76	26.7%
Kerosene	US\$ per liter	0.74	0.98	32.3%
Oil	US\$ per barrel	72.88	107.81	47.9%
Coal	US\$ per gigajoule (GJ)	4.79	12.69	164.8%
Natural gas	US\$ per gigajoule (GJ)	12.32	15.52	26.0%
Electricity	US\$ per kwh	0.16	0.24	45.3%

Figure 1.9: Fuel prices

Fuels:					Coal					
Sectors:					Power sector		Industry		Residential	
Indicators:					Info: supply cost source	Info: retail price source	Info: supply cost source	Info: retail price source	Info: supply cost source	Info: retail price source
country-y	ifscod	countrycd	countryname	year	mit.spsrc	mit.rpsrc	mit.spsrc	mit.rpsrc	mit.spsrc	mit.rpsrc
USA2016	111	USA	United States	2016	5	1	5	1	5	3
USA2017	111	USA	United States	2017	5	1	5	1	5	3
USA2018	111	USA	United States	2018	6	1	6	1	6	3
USA2019	111	USA	United States	2019	6	1	6	1	6	3
USA2020	111	USA	United States	2020	6	1	6	1	6	3
GBR2016	112	GBR	United Kingdom	2016	1	1	1	1	1	1
GBR2017	112	GBR	United Kingdom	2017	1	1	1	1	1	1
GBR2018	112	GBR	United Kingdom	2018	1	1	1	1	1	1
GBR2019	112	GBR	United Kingdom	2019	1	1	1	1	1	1
GBR2020	112	GBR	United Kingdom	2020	1	1	1	1	1	1

Figure 1.10: Prices data quality

filling and sending [this form](#) to the CPAT team so we can update the global CPAT version accordingly.

Check 6: Are prices and percentage changes reasonable?

1.2.8 Distributional consumption effects on households

For distributional results, first, **check if household data for your country is already included in CPAT**; if *not*, process your microdata following the [Codebook and scripts](#) (3-4 days’ resource commitment); if *yes*, define how to transfer revenues (drop-down menu under ‘Policy options’); adjust accordingly if red flags appear. If ‘No’ adjustment for behavioral/structural change is selected, the price increases are fully passed on to the consumer, which may overestimate consumption effects (i.e., the tax-induced mitigation effect is not considered). Alternatively, choose to factor in decile-specific, price-driven demand adjustments/elasticities.

Choose whether distributional effects are expressed based on decile-specific mean or median consumption data: While *median* effects are more representative, some fuels may not be shown if > 50% of households report zero or missing expenses (e.g., due to poor data quality). We recommend that effects not be modeled further than five years out.

Check 7: Make an informed choice on mean/median representation and modelling results without taking into account reduced prices due to behavioral adjustments.

Distributional Module (incidence effects on industries & household consumption)				--> Link to Module			
Targeted transfer options		Other revenue-recycling options		Additional parameters	Presentation of results		
New or existing targeted transfer:	Cash	Public/infrastructure investment:	All Infr.	Adjust for behavioral & structural change?	No	Impacts for mean/avg or median hh in decile?	mean
				Include decile-specific price elasticities?	Yes	Display quantiles in LCU?	No
- targeted percentile	40	Current spending:	Social Protection and La	Emissions-based adj. of product price changes?	Yes	Select year of interest -->	2025
- coverage rate	95	Personal Income Tax (PIT) reduction:	Personal Allowance	Adjust for deadweight losses?	No		
- leakage rate	5	"Targeted Exemption" for bottom XX deciles:	4	Imperfect pass-through?	No		
Transfer to hhs below poverty line (2011 PPP\$/day):	No	Replace missing PIT data, grouping by country:	region	Exempt most-used cooking fossil fuel?	No		
				Exempt cooking fossil fuel for bottom XX deciles:	2		
				NB: fossil cooking fuel is not exempt.			

Figure 1.11: Distributional settings

1.2.9 Contribution of sources to ambient particulate matter

Does the contribution by sector look reasonable? A “reasonable number” should be above 20% and below 90% for most countries. The sectorial distribution could be compared to country level information, if available. If the contribution does not look appropriate when comparing with local information available, the user can change the modeling approach.

The option “Manual-FASST” will allow the user to input their own information, in “Manual inputs tab”. In this case, the user would need to input the contribution of each sector to

Contribution to baseline PM2.5 concentrations by source type in 2018, Poland

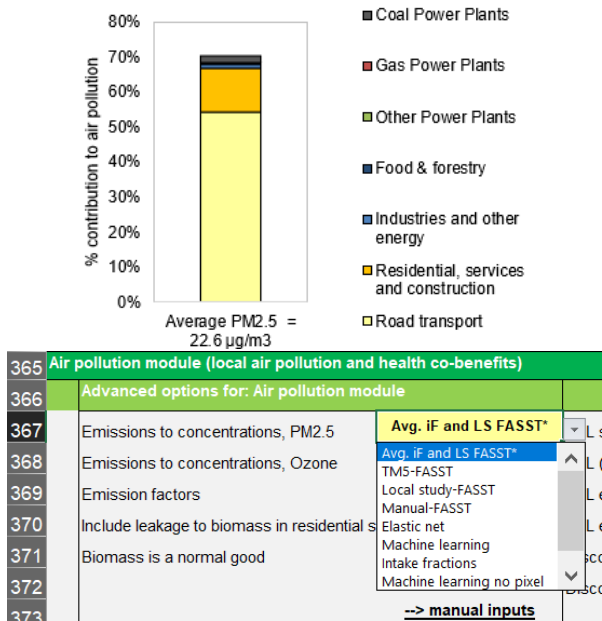


Figure 1.12: Air pollution settings and sources of ambient particulate matter

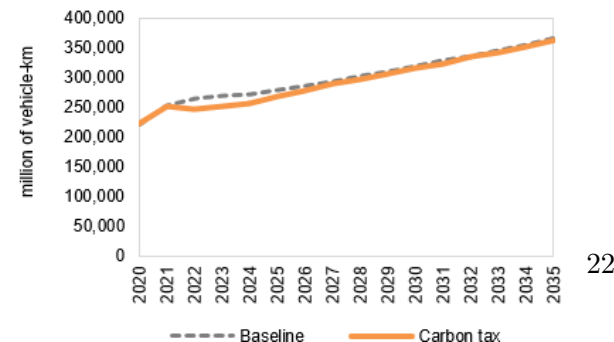
ambient PM2.5. The recommended default option is “Avg. iF and LS FASST”, which uses the average between the intake fractions model and the Local study-FASST approach.

Check 8: Check sectors’ contribution to ambient PM2.5 and adjust modeling approach if needed.

1.2.10 Road transport co-benefits

In the current version of CPAT, total fatalities from road accidents in 2020 are projected based on 2011-2016 data from World Road Statistics. It is recommended that the user checks the validity of this estimate using local data sources, if available, noting that the underlying assumptions can vary significantly from one data source to another. The user might also want to cross-check “forecasted” total distance driven in 2020 (e.g., around 200 billion vehicle-km for Poland as shown in the left-hand side figure) against national statistics, if available.

Total distance driven (for US\$75 per tCO2e in 2030), Poland



Total fatalities from road accidents (for US\$75 per tCO2e in 2030), Poland



1.2.11 Currency used in CPAT

CPAT is presented in constant US dollars (USD). Monetary variables are presented in CPAT are in USD real terms. CPAT distinguishes between the base year – the first year of model calculations (at the time of writing, 2019) – and the year of real terms constant dollars used (at the time of writing, 2021). These settings are defined in the dashboard around cell G60.

CPAT converts between local currencies and US dollars at year of real terms constant dollars (i.e. 2021) exchange rates, and then uses (projected or historical) US inflation indices to deflate in time. For more information on macroeconomic data sources, please see *Appendix A*.

1.2.12 Energy Units in CPAT

CPAT uses commonly used units where possible, rather than adopting a fully consistent (SI) approach:

- For primary and final energy consumption, we use thousand tons of oil equivalent (ktoe) per year.
- For power consumption and generation, we use GWh per year (or TWh per year in some graphs).

For prices we use different units depending on the fuel type:

- For coal, natural gas and biomass, we use \$/GJ;
- For gasoline, diesel, kerosene and LPG, we use \$/liter;
- For crude oil and other oil products we use \$/bbl (dollars per barrel); and
- For electricity we use \$/kWh.

1.3 In-depth use of CPAT

1.3.1 Using CPAT

1.3.1.1 Running CPAT

CPAT is a large Excel file of about 20Mb in compressed Excel binary (.xlsb) format. Its computational needs are substantial, and you should normally not expect to have other memory-intensive programs open. After changing a policy or other input it should take a few seconds to update (you will need to have calculations turned on). You can tell CPAT is working by the ‘graphs updating’. For example, when you change the country and the carbon price input (e.g. by changing cell I6 of the dashboard), the emissions trajectory (around row 44 of the dashboard) will adjust.

CPAT requires a modern version of Excel (2016 at least) and is tested on PC, rather than the Apple Macintosh version of Excel. You should use the desktop, rather than the web version of Excel.

1.3.1.2 Navigating CPAT

You can navigate around CPAT by clicking different tabs. There are three overarching tabs: Cover (this section), Dashboard (the main tab, next section), and User Inputs (following subsection). For the rest of this chapter, we then cover the mitigation module in more detail. After the four main modules of CPAT (mitigation, distribution, air pollution and transport), code readable inputs and outputs of CPAT are presented in MTinput and MToutput tabs (outlined later in this subsection), followed by various data sources driving CPAT, ordered by tab. To get from a graph to the underlying data set driving it, please click on the graph title cell (just above the graph itself) and then use the keyboard to type *Ctrl-\$* on a PC. This will zoom across to the relevant results area and select the cell containing the title. Have a look around (usually below the selected cell) to find the respective data.



Figure 1.14: CPAT Tabs

The subsections can be ‘grouped’ so only one line of results is shown, or ‘ungrouped’ so that all calculations are shown. To group, click the small ‘1’ at the top left of the main window. To ungroup one subsection, click the small + sign on the left-hand side. To ungroup all (not usually needed), click the small ‘2’ in the same place as the ‘1’.

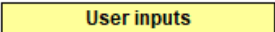
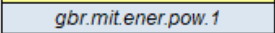







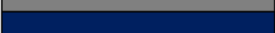
Figure 1.15: Grouping and Ungrouping CPAT sections

1.3.1.3 CPAT visual conventions

CPAT adopts various visual conventions to make the model easier to follow and code. User inputs are colored yellow. Calculations are white. CPAT codes are typically in blue. Tan cells (both lighter and darker shades) represent formulae that are different from those around them and so cannot be dragged or dragged-onto. The cover tab describes these visual conventions.

Contents	
Sheet name	Content
Dashboard	Main user tab - for country selection assumptions for carbon pricing etc.
Manual inputs	(Optional) Manual inputs for parameters where deviating from default e.g. fuel prices, taxes, elasticities etc.
Mitigation	Main module for energy and emissions estimates
Air pollution	Module for estimating effects of emission on local air pollution mortality and morbidity
Distribution	Module for estimating incidence effects on households and industry (deciles, urban vs. rural, etc.)
Transport	Module for estimating effects on congestion, road accidents, and road damage.

Cell color coding	
Color of cells	Content
 User inputs	User input (if the cell is yellow you can change it – if not, please leave it alone!)
 <i>gbr.mit.ener.pow.1</i>	CPAT codes
	Cell with a formula
	Formula that only applies to only one year or changes relative to other rows/columns

Tab color coding	
Color for tabs	Content
	Results and user key user inputs (please only change yellow cells)
	Modules (core models: mitigation, air pollution, distribution, transport)
	Data sources
	Divider (empty tab)

Abbreviations	
Abreviation	Meaning
bn	Billions
mm	Millions
LCU	Local currency units

▶	Cover	Dashboard	Manual inputs	MODULES->	Mitigation	Air pollution	Distribution	Tr
---	--------------	------------------	----------------------	---------------------	-------------------	----------------------	---------------------	-----------

Figure 1.16: CPAT Cover Page

1.3.2 The CPAT dashboard tab

CPAT is controlled by its dashboard which provides the main policy, modelling and parameter inputs, and the main outputs from the policy or policies chosen. The dashboard allows the user to input choices regarding the policy under investigation (such as a carbon tax trajectory, with different options for exemptions and recycling of the revenues, or fossil fuel subsidy reform). The dashboard also has options to allow the user to make different modeling choices (e.g., alternative data sources). The tool produces a series of graphs of the impact of the policy scenarios on several variables, including:

- Policy inputs and headline overall effects;
- Mitigation and energy use (i.e., the reduction in Greenhouse gas (GHG) emissions, changes in energy consumption); macroeconomic and fiscal aggregates (GDP, tax revenues);
- Distributional impacts (per income decile, but also urban/rural, and industrial outputs);
- Air pollution and health (concentration, but also mortality and morbidity); and
- Transport (road fatalities and congestion).

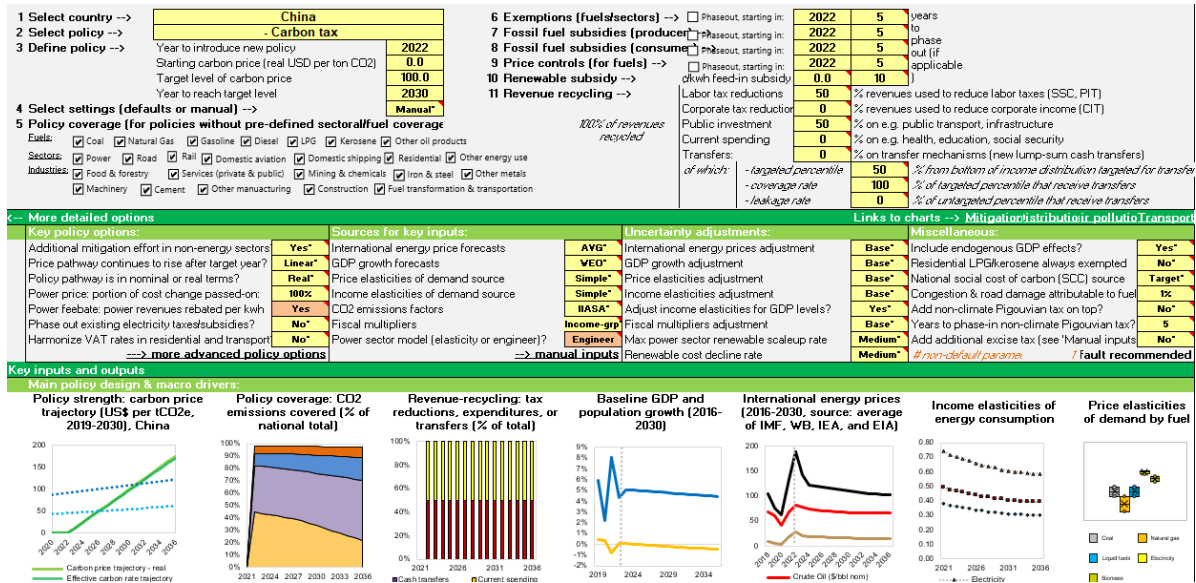


Figure 1.17: Illustration of the CPAT 1.0 Dashboard (partial view, see the excel file for the full dashboard)

In the dashboard, the policy scenario and the baseline are sometimes shown on the same graph, with the baseline shown with a dashed line.

Many CPAT settings have default values. These are usually denoted by an asterisk suffix – e.g. “Yes*“.

1.3.2.1 Policy input area: Country and proposed policy trajectory

At the top left of CPAT, you see various input cells. The yellow cells are user editable. Categorical cells can be altered by clicking the small down arrow. By clicking on the cell which currently shows carbon tax, you can select a different carbon pricing policy (e.g., an ETS), which comes with sectoral exemptions pre-set. All policies are defined by the carbon price. The carbon price trajectory is defined by the introduction date (here 2022), the start level (here \$50/tCO₂), the target level of the carbon price (here \$75/tCO₂), and the year that this target level will be met (here 2030).

On the right-hand side at the top of the dashboard, the user can change settings relating to the phase-out of exemptions, price controls, and subsidies. One can exempt any fuels and sectors from the carbon tax (if unticked). So, if, for example, Kerosene and Cement are unticked, all Kerosene is exempted (independent of the sector), and all Cement energy use is exempted (independent of fuel). It is necessary to ensure that all checkboxes are ticked for full policy coverage (recommended) or unticked as desired. It also includes supplementing policies with renewable energy subsidies and the use of revenues. For revenue recycling, there are five options: labor tax reductions, corporate tax reductions, public investment, current spending, and compensatory transfers to households. The phase-out of exemptions, price controls, and subsidies, as well as the use of revenue, should be as desired by the user.

6 Exemptions (fuels/sectors) -->	<input type="checkbox"/> Phaseout, starting in:	2022	5	years to phase out (if applicable)
7 Fossil fuel subsidies (producer) -->	<input type="checkbox"/> Phaseout, starting in:	2022	5	
8 Fossil fuel subsidies (consumer) -->	<input type="checkbox"/> Phaseout, starting in:	2022	5	
9 Price controls (for fuels) -->	<input type="checkbox"/> Phaseout, starting in:	2022	5	

Figure 1.18: Phase-out policies

1.3.2.2 Policy inputs panel

The first panel shows the result of the policy inputs. This includes **Carbon Price Trajectory**: To check that the suggested carbon tax is in place, please see the policy strength graph under Key inputs and outputs. On default settings, the policy is extended linearly beyond the end date. The dotted lines in the left-hand graph show the range for a carbon price recommended by the High-level Commission on Carbon Pricing. The right-hand graph shows the policy's coverage, including any exemptions (see later for defining exemptions).

There are further graphs in this panel, indicating the use of policy coverage, use of revenue, baseline GDP and energy price assumptions, income and price elasticity assumptions.

The description of both the advanced settings and the settings of the power models are presented in *Appendix F - Parameter options in the mitigation module*.

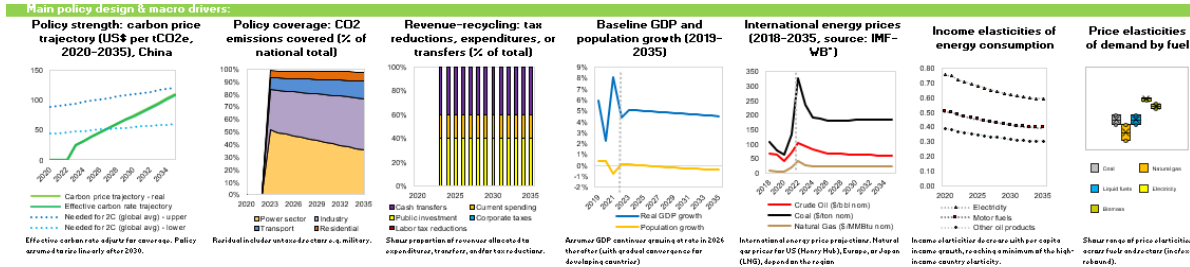


Figure 1.19: Policy design

1.3.2.3 Overview of policies accounted for in CPAT

CPAT covers carbon pricing, taxes, feebates², efficiency policies, fossil fuel subsidy reform, and power-sector-specific policies (e.g., Power Pricing Agreement reform). The main carbon pricing and fossil fuel subsidy reform policies are selected in the main dashboard.

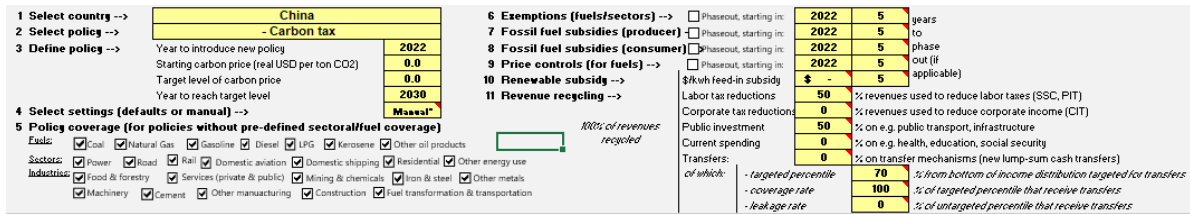


Figure 1.20: Main Policy Dashboard

1.3.2.4 Economy-wide carbon pricing options in CPAT

CPAT accounts for an extensive list of carbon pricing instruments. These can be selected in the 'Policy' box shown below.

1.3.2.4.1 Carbon taxation

This policy represents a carbon tax applied to the supply of all fossil fuels in proportion to their carbon content. It is modeled by adding to the pre-existing tax on a particular fuel a charge equal to the product of the CO2 emissions factor for that fuel and the tax rate on CO2. The carbon tax can be comprehensive in applying to all fuels and sectors, or exemptions can be applied for individual fuels and sectors (with the option to phase out exemptions over time).

²A feebate is a rebated tax which taxes dirty products or activities to subsidize greener products or activities such that net revenue is zero.

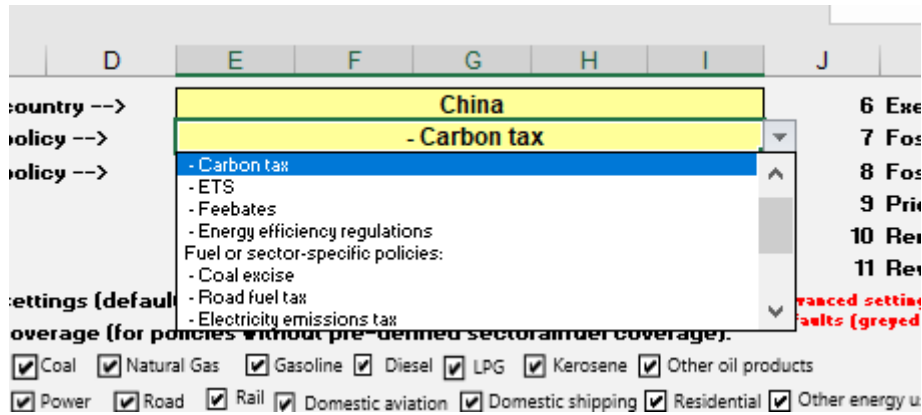


Figure 1.21: Select Policy, CPAT Dashboard

To the extent they are passed on, carbon taxes are reflected in higher prices for electricity. The increase in electricity prices has two components: (i) the pure abatement costs which reflect increase in generation costs per unit due to the shifting to cleaner, but costlier, generation fuels; and (ii) the tax on remaining emissions per unit of production (or carbon charges on fossil fuel inputs per unit of production). The second part can be rebated either by a dedicated policy (see power feebate below) or by a modification of a comprehensive carbon tax.

For carbon taxation and for the other comprehensive carbon pricing schemes, the user can define sectoral or fuel exemptions using the check boxes in the main dashboard.

1.3.2.4.2 Emission Trading Systems

These policies are modeled in a similar way to a tax (CPAT is deterministic and does not capture uncertainty over emissions prices associated with ETSS). That is, CPAT requires the user to estimate the likely price of an ETS and then impose that to find the emissions reduction. That said, there is also a ‘goal seek’ functionality which allows one to change the price in order to meet a particular emissions target in 2030. Because CPAT is set up without macros, the actual goal seek needs to be done by hand set up by the user using in-built Excel goal seek or seeker routine.

A scalar adjustment, set at a default value of 0.9, is applied to the emissions price, which however implies a (moderately smaller) behavioral response from the ETS compared with the equivalent carbon tax with the same price. This scalar could represent: (i) exclusion of small emitting firms from an ETS applied downstream to large firms in the power and industry sectors; (ii) higher price uncertainty under an ETS compared with a tax which potentially dampens investment incentives for low-carbon technologies; and (iii) grandfathering of allowances to incumbent firms creating barriers to new entrants and potentially forestalling innovation.

ETS Goal Seek

Manual Value for Target Carbon Price (link cell I6 to this cell and modify it to reach target)

Sectoral Inclusion::

Power sector

Transport

Buildings

Industry

Other

If yes, proportion of Industry Sector

Percentage or Absolute Target?

Percentage change (usually -ve)

Absolute target

50
Yes
No
No
Yes
No
100%
PercentageReduction
-25%
1,000

Figure 1.22: Goal Seek to Determine (ETS or Carbon Tax) Carbon Price consistent with emissions target

In the dashboard, a goal seek tool is available in order to determine the carbon price matching the emissions target. The goal seek is set around cell Y192 of the dashboard near the panel D of the mitigation section. To use it:

- Connect cell I6 (Target level of carbon price) to be equal to cell AC192 (so that the carbon tax is in the same location as the emissions);
- Define the coverage of the emissions target using the boxes from cell AC194 downwards;
- Define the coverage percentage of industry in the target;
- Define the percentage reduction or absolute emissions target; and
- Modify cell AC192 until cells AB214 and AD214 are as close as possible or set up a goal seek to minimize cell AE214 by changing the target carbon price (cell I6).

GoalSeek	Included	Baseline	Policy Scen.	Proportion In	Target	Diff Squared
Power sector	Yes	4,223	3,163	1		
Transport	No	1,163	1,017	-		
Residential	No	689	492	-		
Industry	Yes	3,905	2,878	1		
Other	No	69	49	-		
Total		8,128	6,042		6,096	2,937

Figure 1.23: Goal Seek to Determine (ETS or Carbon Tax) Carbon Price consistent with emissions target

The goal seek only works for 2030 emissions and can be used for NDC or for ETS targeting.

Note that CPAT models *new* ETSs and Carbon Taxes separately from *existing* ETSs and Carbon Tax. For the European Union countries for example, the existing ETS price are

projected forward: the growth rate in this projection can be set in the dashboard. It should also be noted that new ETSs are modeled as a sector being ‘in’ or ‘out’, whereas existing ETSs use an aggregated percentage of industry and power based on aggregated coverage data. When a sector is partly included, the carbon price is proportionally reduced by the coverage proportion and the reduced carbon price is applied to the whole sector.

1.3.2.4.3 Feebates

In their pure form, feebates provide a revenue-neutral, sliding scale of fees on activities (like power generation) or products (like vehicles). Activities or products with above average emission rates pay a net tax; activities or products with below average emission rates get net revenues. When a feebate is constructed by a carbon tax plus a rebate based on output (e.g., kWh electricity produced, steel produced, etc.) this is called Output Based Rebating (OBR). But there are other feebates differing from this form, for example when the feebate is on the initial purchase decision, rather the ongoing use (e.g., in the case of vehicles).

In most cases, feebates are modeled through shadow prices. Shadow prices are modeled not by a change in prices per se but rather a price-like adjustments to energy use equations. These shadow prices affect the efficiency channel of the energy use (typically about half the overall price-based effect) but not the usage channel.

Power supply feebates are modeled as a rebated carbon tax (i.e. a carbon tax that only increases power prices through pure abatement costs, not the cost of emissions).

1.3.2.5 Sectoral carbon pricing and taxation policies

Coal excise tax. The coal excise tax is a carbon tax (in the sense of it being defined per ton CO₂) only on coal.

Electricity emission tax. This imposes a carbon tax on the electricity sector.

Electricity excise. This is a tax per kWh of electricity used. We set the tax via the standard carbon tax interface. The tax in \$/tCO₂ is mapped to one per kWh using the year one emission factor as a conversion factor. However, this is only a tax on end users of electricity, it does not distinguish between different ways of generating electricity, incentivizing only electricity demand and not the composition of electricity supply.

Power feebate. This policy covers power supply feebates if the engineer model is selected and covers power usage feebates if the elasticity model is selected.

Vehicle fuel economy. This imposes shadow prices (similar to a feebate) in the vehicle sector.

Road fuel tax. Taxes imposed on all fuels in the road transport sector.

Sectoral fossil fuel excise taxes. These can be modeled by the user, using this setting in the dashboard. This allows the user to set sector- and fuel-specific carbon taxes.³

Figure 1.24: Excise Reform Settings

The actual sectoral-fuel tax rates are set in the ‘Manual Inputs’ tab.

Figure 1.25: Excise Reform Settings

1.3.2.6 Regulations and subsidies

Energy efficiency regulations. CPAT can model CO2 emission rate standards per kWh of power generation, per unit of production for individual industries, or per vehicle kilometers traveled (VKT) for vehicles, or energy efficiency standards for electricity demand, and energy use in the industry, transport, and building sectors. These policies reduce the emissions or energy

³To convert a carbon tax to an excise duty, please see emissions factors available in the mitigation module.

intensity of a sector but without the same demand response (e.g., reductions in VKT) as under carbon pricing because they do not involve the pass through of carbon tax revenues (or allowance rents) in higher prices (e.g., for electricity or gasoline) – they also produce a partially offsetting increase in emissions through the rebound effect. In particular, CPAT focuses on residential and industrial efficiency regulations.

Clean technology subsidies. Subsidies for renewable generation are modeled in CPAT by a subsidy providing a proportionate reduction in the per unit generation cost for renewables. Subsidies for electric vehicles (EV) are not explicitly modeled in CPAT.

1.3.2.7 Fossil fuel subsidy reform and regulated price reform

CPAT includes extensive capabilities to reform fossil fuel subsidies. For each form of subsidy (i.e., producer-side and consumer-side) one can select the phase out check box and then the number of years to phase out that subsidy. CPAT also includes some estimations of price controls, which can also be phased out (although there are interaction effects so doing both at the same time is not advised). We recommend the default assumptions for fossil fuel subsidies to be checked and/or replaced by the user (user defined subsidies are defined in the manual inputs tab and the dashboard or mitigation tab – the `dom_prices` tab contains the default assumptions on prices and subsidies). For more information, see the Section *Fuel prices, taxes and subsidies* and Sub-Section *Fiscal revenues* of this chapter. Note that whether fossil fuel subsidy reform is included in the baseline is in the advanced settings. The user should check the following setting:

Category	Phaseout, starting in:	Year	Years to phase out (if applicable)
6 Exemptions (tueis/sectors) -->	<input type="checkbox"/>	2022	5
7 Fossil fuel subsidies (producer) -->	<input type="checkbox"/>	2022	5
8 Fossil fuel subsidies (consumer) -->	<input type="checkbox"/>	2022	5
9 Price controls (for fuels) -->	<input type="checkbox"/>	2022	5

Figure 1.26: Excise Reform Settings

1.3.2.8 Power sector-specific policies

CPAT has the capability to adjust the maximum rate of renewable scale up. This is set for default to 2% for wind and 2% for solar, meaning that we could add (gross of retirements) additional generation equal to 2% of the total for each generation type. For many countries, this growth rate is too ambitious, and a tighter cap will be needed. On the other hand, more ambitious renewables policies could lead to this cap being loosened. This constraint is the same in the baseline and the policy scenario.

capture and storage), emission rate policies for non-road vehicles, measures for extractive industries (e.g., moratoria on extraction, charges on production or fugitive emissions), and mitigation instruments beyond the energy sector. Broader policies to promote R&D into critical technologies are also beyond the scope of CPAT.

1.3.2.10 Metrics for comparing policies

The CPAT Dashboard provides a series of results that can be used to compare policies across different dimensions. The main metrics are described below.

CO₂ emissions. CO₂ emissions are given by the consumption of each fossil fuel product, aggregated across sectors, multiplied by the CO₂ emissions factor for that fuel product, and then aggregated across different fossil fuel products.

Revenue. Revenues from carbon mitigation policies are calculated net of indirect changes in revenues (or outlays) from pre-existing energy taxes (or subsidies). Direct revenues from carbon pricing are simply the carbon price times the CO₂ emissions to which they are applied and, in the case of ETSs, the fraction of allowances that are auctioned (rather than freely allocated). Revenues from pre-existing energy taxes are the product of the prior fuel tax rate (which is negative in the case of fuel subsidies) and the fuel consumption to which they are applied, aggregated across fuels and sectors, plus the product of any electricity tax and the electricity consumption to which it applies. Indirect revenue losses from carbon pricing are the difference between revenues from pre-existing energy taxes before and after carbon pricing. Similarly, revenues from new, or increases in existing, energy taxes are the tax increase times the fuel or electricity to which the increase applies, net of indirect revenue changes from pre-existing energy taxes.

For regulations and revenue-neutral feebates there is no direct revenue, though there is generally an indirect revenue loss as these policies erode bases for pre-existing energy taxes. For renewable and clean technology subsidies, there is a direct revenue loss equal to the product of the subsidy rate and the base to which it applies plus indirect revenue losses from pre-existing energy taxes.

Externalities. CPAT estimates externalities due to improved human health (because of reduction in air pollution), reduced road accidents, reduced travel time and reduced road maintenance costs. Please refer to the *Air Pollution* and *Transport* chapters for more information on the externalities calculation.

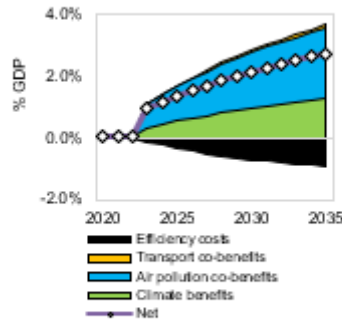
Distributional effects. CPAT also offers an incidence analysis about the consumption effects that household could experience after a carbon pricing policy. The details can be consulted in the *Distribution* chapter.

GDP Effects. GDP growth will be affected by carbon pricing and the total impact will depend on how the revenues are used and other assumptions and parameters used in CPAT. Please refer to the *Output* section for details.

Climate benefits. The climate benefits are linked to the GHG emission reductions that can be achieved with a policy and the social cost of carbon. For details on emissions calculations and the social cost of carbon in CPAT, please refer to Chapter 3 on the Mitigation Methodology.

Using the previous metrics, the Section **Monetized welfare benefits** discusses the estimation of the monetized domestic environmental costs from fuel use. The domestic environmental co-benefits of mitigation policies are calculated by the induced reductions in use of a fuel product in a particular sector, multiplied by the corresponding domestic environmental cost per unit, and aggregated across sectors and fuels. Efficiency costs of policies reflect losses in producer and consumer surplus in fossil fuel markets, which in turn correspond to areas under marginal abatement cost schedules – they can be interpreted as the annualized costs of using cleaner, but costlier technologies, and of reducing energy consumption below levels households would otherwise prefer. Efficiency costs are calculated using applications and extensions of long-established formulas in the public finance literature (e.g., Harberger, 1964) based on second-order approximations. These formulas can be applied with data on the size of tax distortions in fuel and electricity markets, any induced quantity changes in markets affected by these distortions (an output from the model), and any new source of price distortion created by carbon policies.

**Total monetized welfare benefits for
US\$75 - Carbon tax p/tCO2e by 2030,
China**



Shows monetized net welfare benefits. Economic costs are deadweight losses from the tax before revenue recycling. Economic costs do not include revenue recycling and tax interaction effects.

Figure 1.28: Monetized Welfare Benefits in CPAT Dashboard

1.3.2.11 Headline projected effects panel

The main outputs are shown under Headline projected effects, in Panel B in CPAT Dashboard. Starting from the left, these graphs show:

1. GHG emissions relative to baseline (dashed line) & NDC target (dotted horizontal line);

2. Fiscal revenues (before recycling of funds);
3. Impact on projected GDP growth;
4. Impacts on households (note: only countries for which household data are available);
5. Co-benefits: Averted air pollution & road accident deaths; and
6. Total monetized benefits from the policy.

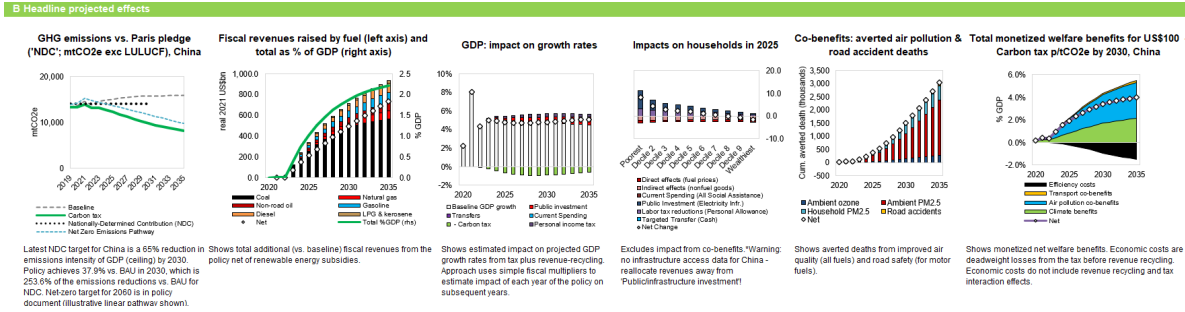


Figure 1.29: Main outputs, Dashboard tab

1.3.2.12 Advanced settings

Advanced settings can be defined throughout the Dashboard, related to the different CPAT modules. The settings are displayed by clicking the + button to expand.

For instance, for the Mitigation module, the first panel of advanced settings is around row 16 and includes key policy options, sources for key inputs, uncertainty adjustments and miscellaneous effects.

Key policy options:	Sources for key inputs:	Uncertainty adjustments:	Miscellaneous:
Additional mitigation effort in non-energy sectors? Yes*	International energy price forecasts AVG*	International energy prices adjustment Base*	Include endogenous GDP effects? Yes*
Price pathway continues to rise after target year? Linear*	GDP growth forecasts WEO*	GDP growth adjustment Base*	Residential LPG/kerosene always exempted No*
Policy pathway is in nominal or real terms? Real*	Price elasticities of demand source Simple*	Price elasticities adjustment Base*	National social cost of carbon (SCC) source Target*
Power price: portion of cost change passed-on: 100%	Income elasticities of demand source Simple*	Income elasticities adjustment Base*	Congestion & road damage attributable to fuels 1%
Power feedbate: power revenues rebated per kWh Yes	CO2 emissions factors NASA*	Adjust income elasticities for GDP levels? Yes*	Add non-climate Pigouvian tax on top? No*
Phase out existing electricity taxes/subsidies? No*	Fiscal multipliers Income-grp*	Fiscal multipliers adjustment Base*	Years to phase-in non-climate Pigouvian tax? 5
Harmonize VAT rates in residential and transport? No*	Power sector model (elasticity or engineer)? Engineer*	Max power sector renewable scaleup rate Medium*	Add additional excise tax (see 'Manual inputs' tab)? No*
more advanced policy options	manual inputs	Renewable cost decline rate Medium*	non-default parameters ! = default recommended

Figure 1.30: General settings

The mitigation module also has wide range of advanced options which are covered around row 58. For example, the user has an option to specify existing ETS permit price growth for future years, can choose to apply the same VAT tax rate in the residential and transport sectors if it is different from the general VAT in the economy, adjust social cost of carbon tax and more.

The dashboard includes advanced parameter options for the power models around row 109. This includes, for example, information on the proportion of fossil-fueled generation that is covered by power purchase agreements (PPAs), an important measure of how inflexible the power sector is to prices due to market structure factors. To access this panel, click the plus sign to ungroup.

57 Mitigation module (macro & energy effects)		--> link to module			
58 <-- Advanced mitigation options					
59	General assumptions		Additional policy-induced efficiency gains pa by sector	Apply existing non-carbon taxes?	Energy pricing assumptions
60	First year of model calculations?	2019	Power	Coal	Use manual domestic energy prices?
61	Normal results in real terms of which year?	2021	Road vehicles	Natural gas	Use uniform global assumption for fuel prices (norm)
62	Use energy balances or (CPAT) energy consumption data?	Balances	Residential	Gasoline	Externalities are part of VAT base for optimal taxes?
63	Generate Matrix of Energy Consumption Projections for NDC submission	2019	Industrial	Diesel	Phase out Subsidies
64	Use 'world' (USA) or country-specific discount factors?	Latest	Feebates	Other oil products	Share of subsidies to phase-out in the policy scenario?
65	Sum all oil products in industrial transformation sector?	World	Adjustment to efficiency margins for shadow pricing policies:	LPG	Apply phaseout in the baseline scenario?
66	Adjust Annex I country energy-related CO2 EFs to match NDC submission	Converted	Energy efficiency regulations	Kerosene	Period to reach full phaseout (baseline scenario)
67	Adjust non-Annex I country energy-related CO2 EFs to match NDC submission	Yes*	Vehicle fuel economy	Biomass	Share of subsidies to phase-out in the baseline scenario?
68	Info: adjustment to EFs	Yes*	Residential efficiency regulations	Electricity	Consumer-side subsidy
70	Industrial process emissions scale with industrial CO2 emissions	0.98	Industrial efficiency regulations	Existing carbon tax	Share of subsidies to phase-out
71	LULUCF emissions decline at % pa (in absolute value of global energy demand scenario)	3%	Residential Substitution Implicit Efficiencies	Apply existing carbon tax (if exists)?	Apply phaseout in the baseline scenario?
72	Social cost of carbon (SCC) assumptions:	SBREG	LPG	Assumed Chart Area	Period to reach full phaseout (baseline scenario)
73	Target-consistent carbon price by 2030 (for 'Target' option)	0.98	Kerosene	Override base + 3 year with current/forecast	Share of subsidies to phase-out in baseline
74	NSCC elasticity of marginal utility (μ)	75	Biomass	Existing ETS	Price liberalization
75	NSCC elasticity of marginal utility (μ)	2%	NatGas	Apply existing ETS (if exists)?	Government energy price controls
76	Global social cost of carbon (GSCC) source	1.5%*	New ETS	Existing ETS permit price growth per annum (real terms)	Phase-out price controls in the baseline?
77	SCC (both NSCC and GSCC) - annual rise in real terms	Target*	ETS behavioral responses and revenues adjustment	New carbon tax complementary to existing ETS coverage	
78		4%		Override base + 3 year with current/forecast	
				USD EU-ETS price in base + 3 year (projected fwd)	

Figure 1.31: Advanced Mitigation Options

B Power sector (Average* Model)		Year of interest for power sector costs -->				2030
<-- Advanced power sector options						
Elasticity Model Parameters:		Demad	Please enable/restrict new investments in power:		WACC override (if not tech-specific) -->	
Elasticity model uses economy-wide or sectoral power demand?	Economy	Use Elasticity Model Power Demand in Engineer Model	Coal	Max invest? Online or n	Adjust?	Override
Use old or new generation costs in elasticity model?	New*	Subsidies	Natural gas	If Present* 2019	Ma*	Zc
Engineer Model Parameters:		Baseline renewable energy subsidy, \$/kwh nom	Oil	If Present* 2019	Ma*	Zc
Dispatch		Apply additional RE subsidy to hydroelectric power?	Nuclear	If Present* 2019	Ma*	Zc
k Parameter dispatch	2	Minimum (post subsidy) generation cost \$/kwh real	Wind	If Present* 2030	Ma*	Zc
Use Spot Fuel Prices in Engineer Power Model	No*	Storage	Solar	Yes 2019	Ma*	Zc
Maximum Coal Capacity Factor	30%	Percent allocation of ST storage costs to VRE	Hydro	Yes 2019	Ma*	Zc
Maximum Gas Capacity Factor	30%	Total hours short term storage for 100% VRE	Other renewables	If Present* 2030	Ma*	Zc
Override capacity factor outside of:		kwh storage to kw interface ratio (hours)	Biomass	If Present* 2019	Ma*	Zc
Min (Sol/Wnd)	15.0%	Percent allocation of LT storage costs to VRE				
Min (Others)	1.0%	Starting point of long term storage requirement (%VRE)				
Max (all)	100.0%	GW electrolyzer per Gwly for 100% VRE (%)				
PPAs		kwh of LT storage per kW electrolysis				
Proportion of PPAs in coal and gas Generation	0.0%	Retirement				
Phase out any coal and gas PPAs?	Yes*	Maximum cost based early coal retirement proportion				
Phase out of PPAs begins	2023	Hydro retirement rate set to zero				
Phase out coal and gas PPAs over n years?	2	Investment				
Calibration		k Parameter investment				
Use additional coal intangible cost	Yes*	WACC: User-, Income- or Tech-dependent?				
Manual Value for coal intangible cost (base year)	0	If User-selected global WACC, what value?				
Manual Value for coal intangible cost (2030)	0	Minimum WACC				
Use Engineer Covid Adjustment (If Yes 0=No)	0	Max coal/gas invest as a percentage of total gen				
		Max hydro/renew/other invest as a percentage of total				
		If used, user-defined maximum Wind/Solar Scalup				

Figure 1.32: Power model settings

1.3.2.13 Mitigation module: Advanced settings and detailed results

The mitigation module panels show the following results:

1. Energy baseline externalities, prices, consumption, and targets;
2. Power sector results;
3. Fiscal, macroeconomic, and welfare effects;
4. GHG emissions and short-lived climate pollutants (SLCPs); and
5. Energy-related CO2 emissions by fuel & sector (power, industries and transport).

The baseline externalities, prices, consumption and targets panel contain information about estimated externalities, energy price changes induced by the policy, and projected and efficient price change. One can select the ‘year of interest’ in the top right of the panel. The lower row shows sectoral and fuel energy consumption changes (the baseline is with the dotted line), changes induced by the policy and national sectoral NDC targets.

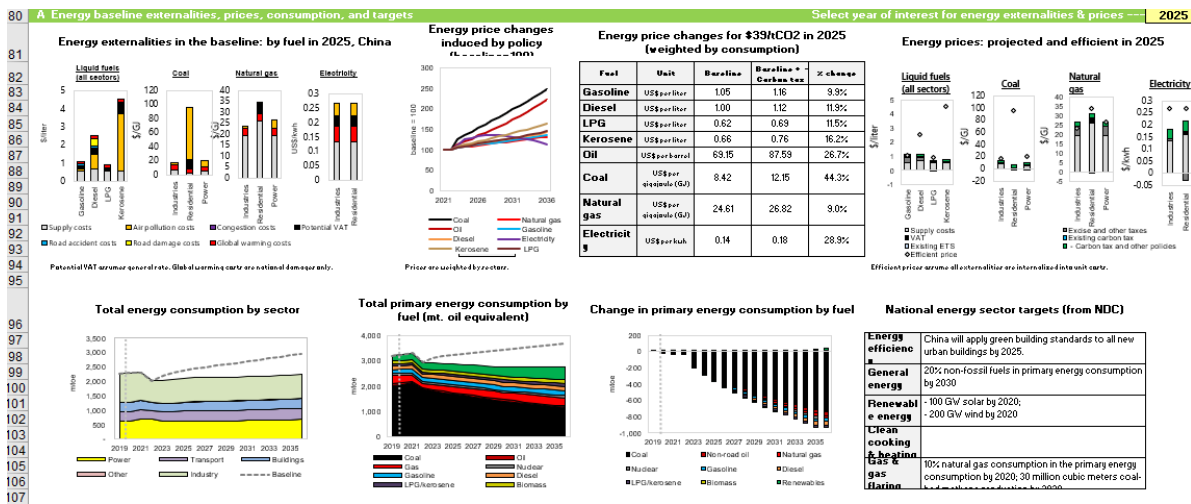


Figure 1.33: Prices Panel

The CPAT power panel contains information about the electricity system. The graphs are shown below. One can select the ‘year of interest’ in the top right of the panel. CPAT has two power models: the elasticity-based and technoeconomic (engineer) models, with the default set to the average between the two. However, the more CPAT can be tailored by the user to country-specific settings, the more the user is encouraged to use the ‘engineer’ choice (this is selectable on cell L24 in the original ‘more detailed options’ panel).

The fiscal effects contain notably the multipliers used in CPAT (bottom left) - the default is MFmod multipliers. The bottom middle shows the net GDP effects in time.

The emissions panel shows a deep dive into GHG emissions.

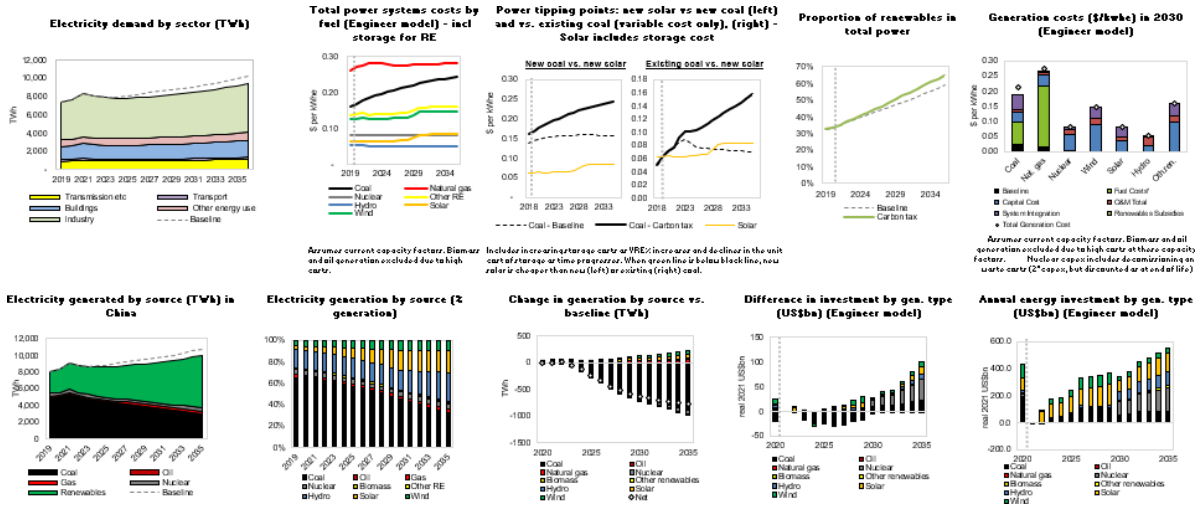


Figure 1.34: Power model settings

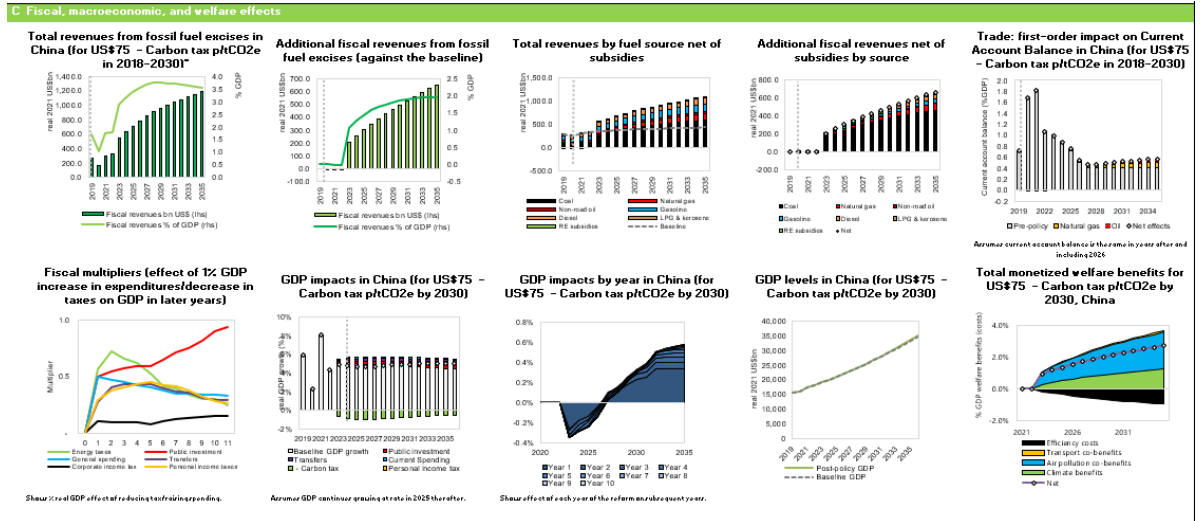


Figure 1.35: Fiscal, macroeconomic and welfare effects

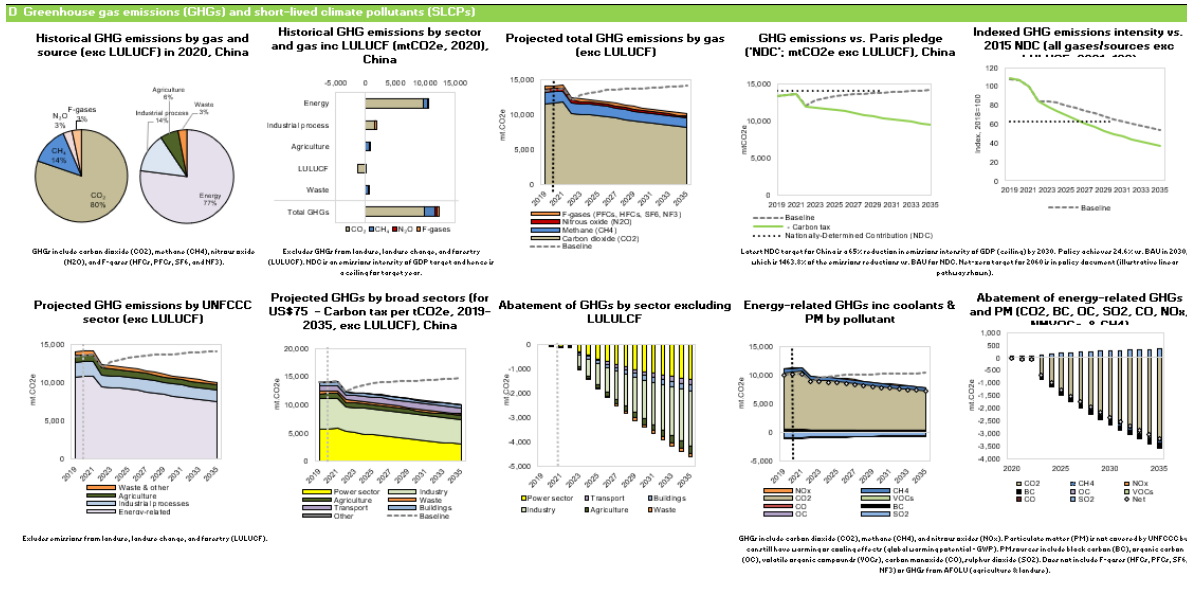


Figure 1.36: GHG and short-lived climate pollutants panel

The energy related emissions show a deep dive into CO2 and other energy-related emissions including the Kaya identity which disaggregates the drivers of emissions changes.

1.3.2.14 Distributional consumption effects on households

For distributional results, first, check if household data for your country is already included; if yes, define how to transfer revenues (dropdown in ‘Policy options’); adjust accordingly if red flags appear. If ‘No’ adjustment for behavioral/structural change is selected, the price increases are fully passed on to the consumer which may overestimate consumption effects (i.e. tax-induced mitigation effect is not considered). Alternatively, choose to factor in decile-specific price-driven demand adjustments/elasticities.

Choose representation of means or medians: while median effects are more representative, some fuels may not be shown if >50% of households report zero or missing expenses (e.g., if poor data quality). Make an informed choice on mean/median representation and modelling results with/out taking into account reduced prices due to behavior adjustments.

For more information, please see the distribution chapter of CPAT documentation.

1.3.2.15 Air pollution (and associated health effects) results

The recommended default option to estimate concentration changes is “Avg. *iF* and *LS FASST**” or “Local study-FASST”. See the air pollution methodology chapter for more de-

E Energy-related CO2 emissions by fuel & sector [power, industries, transport]

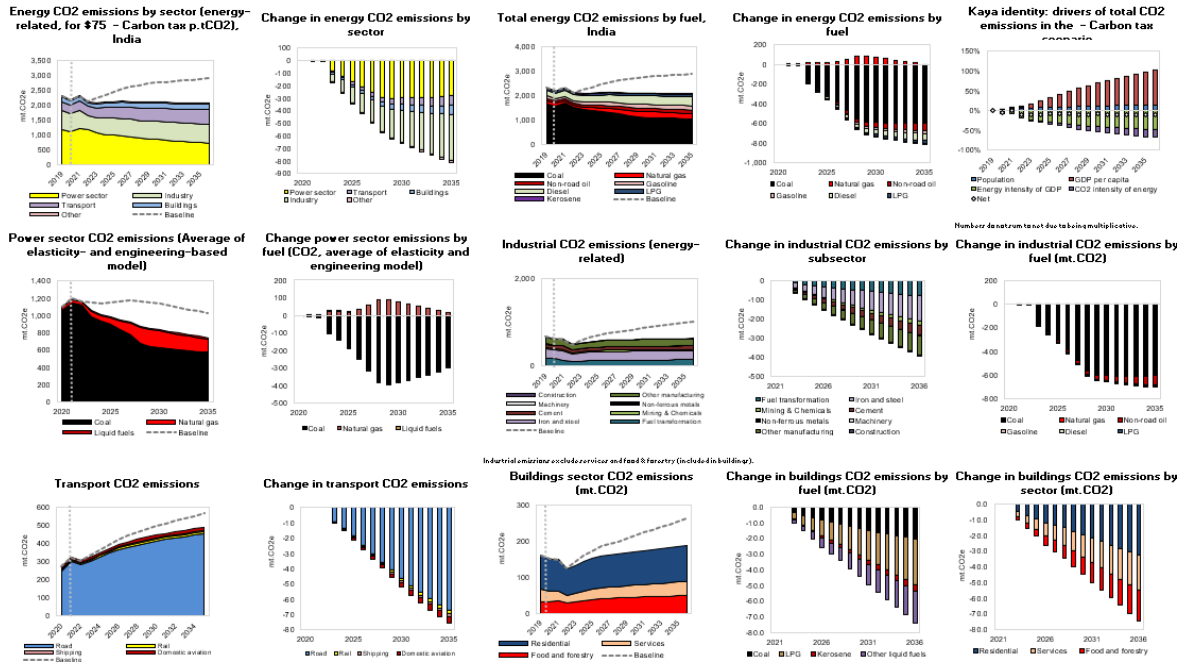


Figure 1.37: Energy-related emissions

Distributional Module (effects on industries & household consumption)				Presentation of results		-> Link to Module	
Targeted transfer options		Other revenue-recycling options		Additional parameters		Presentation of results	
250	New or existing targeted transfer:	Cash	Public/infrastructure investment	Electricity Infr.	Adjust for behavioral & structural change?	No	Impacts for average or median hh in decile?
251					Include decile-specific price elasticities?	Yes	Display quantiles in LCU?
252	- targeted percentile	50	Current spending:	All Social Assistance	Adjust GTAP-implied CP revenues to CPAT?	Yes	Select year of interest ->
253	- coverage rate	100			Adjust for deadweight losses?	No	
254	- leakage rate	0	Personal Income Tax (PIT) reduction:	Personal Allowance	Imperfect pass-through?	No	
255	Transfer to hhs below poverty line (2011 PPP\$/day):	No			Exempt most-used cooking fossil fuel?	No	
256			"Targeted Exemption" for bottom XX deciles:	2	Exempt cooking fossil fuel for bottom XX deciles:	1	
257			Replace missing labor tax data, grouping by country:	region	INB: non-biomass cooking fuel is not exempt.		
258							
259							

Figure 1.38: Distributional settings

tails on what the different options entail. Is important to check the sectors' contribution to ambient PM2.5 and adjust modeling approach if needed.

As in the other sections of CPAT, the cells in yellow can be modified by the user. For instance, the user can input a local Value of the Statistical Life to value air pollution externalities from fossil fuels.

364 Air pollution module (local air pollution and health co-benefits)			
365 Advanced options for: Air pollution module			
366	Emissions to concentrations, PM2.5	Avg. iF and LS FASST*	VSL source Transfer from OECD
367	Emissions to concentrations, Ozone	TM5-FASST	VSL (where manual source, constant 2021 \$USD) \$500,000
368	Emission factors	Average	VSL elasticity source Income group
369	Include leakage to biomass in residential sector	No	VSL elasticity (where manual source) 1
370	Biomass is a normal good	No	Discount rate selection 3% (Robinson 2019)
371			Discount rate (where manual source) 3%
372		--> manual inputs	--> advanced calibration options

Figure 1.39: Air Pollution settings in CPAT Dashboard

Some additional parameters can be modified in the “Manual inputs” tab. A link to this tab is at the end of the air pollution settings in the Dashboard. In that tab, the user can input source apportionment information, that reflects the sectoral contribution to ambient PM2.5 in the analyzed country. Notice that for CPAT to use that manual input, the “Emissions to concentrations, PM2.5” parameter needs to be set to “Manual-FASST”.

For more information, please see the air pollution chapter from CPAT documentation.

1.3.2.16 Transport co-benefits (road accidents, congestion, and road damage)

The group of panels shows the results for transport co-benefits. This includes results for distance traveled, fatalities on the road, congestion, fuel prices and the statistical relationship between fuel prices, accidents and congestion.

For more information, please see the transport chapter of this documentation.

1.3.3 Manual inputs tab: Tailoring CPAT

CPAT is designed to be able to be run ‘off the shelf’. Nevertheless, the default settings will usually need to be checked and tested for the country context. In particular:

- The prices and subsidy information should be checked and, if needed, augmented on the manual settings tab.

- The user can set the investment trajectory in the power sector, both in the baseline and the policy scenarios. For more information, please see the CPAT quick-start guide.

Most of these tailored inputs are stored in the manual inputs tab. This tab also gives the option to add any combination of additional fuel- and sector-specific taxes (excise reform section).

	B	C	D	E	F	G	H	I	
1	CPAT Manual inputs			Links ---->	Dashboard				
2	Explanation: this tabs allows for more precise tweaking of inputs and assumptions where manual data is available								
3	NB: Please change only yellow cells and check that the units are correct.								
4									
5	Domestic energy prices & taxes				Energy prices & taxes set to 'manual'? (see Advanced options in 'Dashboard')	No			
113									
114	Excise reform		Additional excise tax set to 'yes'? (see Dashboard) -->			No	real 2021		
130									
131	Domestic energy price controls				Energy price controls set to 'manual'? -->	Yes			
148									
149	Market-induced imperfect pass-through (for Distributional results only)								
164									
165	Energy price forecasts		International energy prices set to 'Manual' option?			No			
174									
175	GDP & population forecasts		GDP growth forecasts set to 'Manual' option?			No			
180									
181	Social cost of carbon (SCC)		SCC set to 'Manual' option?			No			
189									
190	Local air pollution source apportionment								
203									
204	Fiscal multipliers		Multipliers set to 'Manual' option?			No			
217									
218	Elasticities		Income elasticities source set to 'manual'? ->		No	Price elasticities ->	No		
276									
278	Additional mitigation effort in non-energy sectors				Effort set to 'manual'? ->		No		
288									
289	Enable new investments		New investments set to 'Manual' option on dashboard? ->			No	Investment		
319									
320									

Figure 1.40: Manual Inputs tab

1.3.4 Navigating other CPAT tabs

Each module is divided into sections (dark green) and subsections (light green). As mentioned earlier, subsections can be ‘grouped’ so only one line of results are shown, or ‘ungrouped’ so that all calculations are shown. To group, click the small ‘1’ at the top left of the main window. To ungroup one subsection, click the small + sign on the left-hand side. Note that in CPAT, codes have the following format:

*Country.Tab.Variable.Sector.FuelType.Other.SubscenarioNumber*⁴

Users may wish occasionally to change the coding of CPAT itself. In this case it is noted that CPAT is designed in such a way that the whole of part C (the baseline scenario) can be copy-pasted into part D (the policy scenario) or vice versa. It however important not to copy the first, dark green row of part C (D) which designates the baseline (the policy implemented). Note also that due to computational limitations, for the Mitigation module, part C should be copy-pasted into part D, subsection by subsection, rather than all at one time. More information on coding or modifying CPAT is available on request.

⁴Other’ varies by context – it can mean pollutant in the air pollution module or submodel (ie engineer/elasticity) in the power module.

To ensure CPAT is copy-pastable, three principles must be covered:

- There should be **no references between C and D**
- References to other sections than C and D or to other tabs **must be row-absolute** (e.g. 'MTInputs!\$F\$212')
- References within a submodule (C) to other parts of C **must be row-relative** (without a \$ before the row number – e.g. 'MTInputs!F\$212')
- References in the results are referring to C and D **must use an 'Index-match'** based on the CPAT code. This means that the user should:

1. Define a helper row (or column if needed) number, using the MATCH function in Excel based on the CPAT code.
2. Use the INDEX function in Excel.

1.3.4.1 The Mitigation tab

The following figure shows the organization of the mitigation module.

Figure 1.41: Mitigation module: Overview

The mitigation module is divided into several sub-sections:

- **Part A: Overview.**
- **Part B: Key Assumptions and inputs.** This section comprises assumptions used and data inputs (i.e. macro data, elasticities, energy consumption, domestic and international prices, etc.)

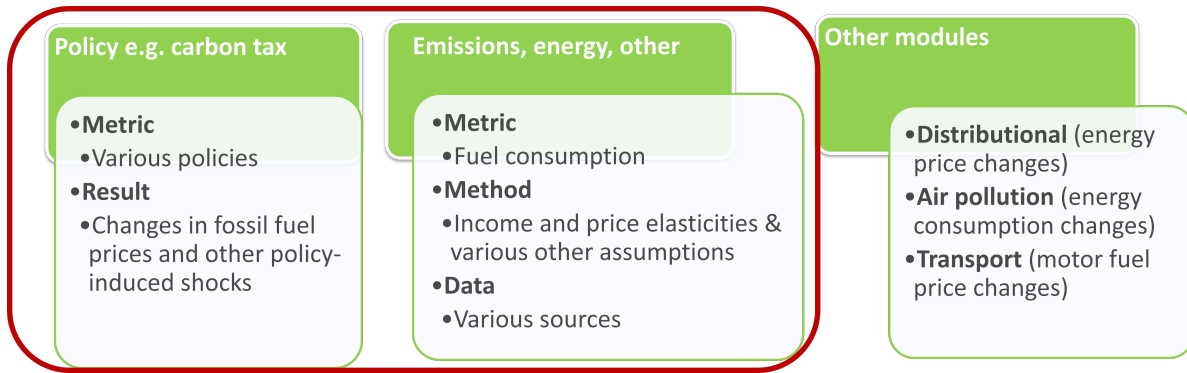


Figure 1.42: Mitigation module: Overview

- **Parts C and D: The main model repeated twice (baseline and policy – usually a carbon tax).** In particular, part C holds for the baseline scenario and part D for the policy scenario. These parts are identical, except that part D accounts for the policy implemented. These sections build the two power models (based on prices inputs) and calculates the energy use across the main sectors (i.e. industry, building, transport, and other energy use), as well as the associated emissions. The sections also provide estimates on the fiscal revenues resulting from the policy in place and associated GDP effects.
- **Parts E and F: The results areas.** Finally, parts E and F summarize all the results to create the graphic visualization. This area cannot be ‘grouped’ as then otherwise parts of graphs that rely on these data would not be visible.

1.3.4.2 The Distribution tab

The organization of the Distribution module is shown in Figure 1.43.

The Distributional effects module is divided into the following sections:

- **A: Module overview:**
 - **A.I. Description.** This sub-section provides a brief flow chart-style outline of the Distribution module (see Figure 1.44):
- **A.II. Country coverage.** This sub-section lists the WB member countries, for which analytical outputs are available in the CPAT Distribution module.
- **B: Key Assumptions and inputs.** This section includes: 1) module assumptions, e.g., years of reference, macro variables, scaling factors for calibration to national accounts data, etc. (sub-section B.I); 2) sector- and energy product-specific percent price changes from the Mitigation module used in the analysis (sub-sections B.II and B.III); and 3) cost/price pass-through coefficients (sub-section B.IV.).

Distributional Effects Module – Malaysia	
A.	Module overview
A.I.	Description
A.II.	Country coverage
B.	Key assumptions and inputs
B.I.	Key assumptions
B.II.	Energy price change data
B.III.	Price change calculations
B.IV.	Cost pass-through assumptions
C.	Carbon tax
C.I.	Price changes from policy scenario
C.II.	Price elasticities of demand, behavioral/structural change and deadweight loss (DWL) adjustments
C.III.	Household budget shares – direct fuel consumption
C.IV.	Household budget shares – indirect fuel consumption
C.V.	Consumption losses – direct effects
C.VI.	Consumption losses – indirect effects
C.VII.	Consumption losses – total effects
C.VIII.	Household survey-to-national accounts adjustments
C.IX.	Change in Gini coefficient
C.X.	Targeted cash transfers, public investment and current spending
C.XI.	Personal income tax (PIT) reductions
D.	Outputs for charts
D.I.	Chart labels

Figure 1.43: Distribution module organization

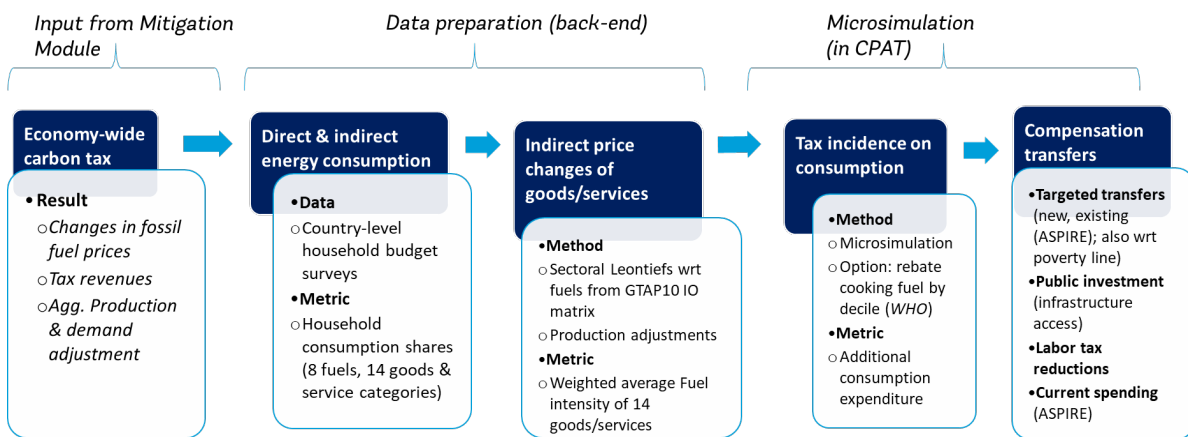


Figure 1.44: Distribution module description

- **C: Climate policy scenario (e.g., Carbon tax).** This section includes the distributional effects (consumption incidence) analysis and related calculations. Specifically, it is divided into: 1) calculations of the definitive energy and non-energy price changes used in the analysis (sub-section C.I); 2) various adjustments to the incidence effects analysis, based on user inputs (e.g., decile/product-specific price elasticities of demand, behavioral and structural change adjustment, etc.) (sub-section C.II); 3) household budget shares for fuel (sub-section C.III) and non-fuel (sub-section C.IV) consumption; 4) incidence effects from fuel (sub-section C.V), non-fuel (sub-section C.VI) and total (sub-section C.VII) consumption; 5) calibration of data to national accounts (sub-section C.VIII); 6) effects on inequality (sub-section C.IX);
 - 7) compensation schemes via transfers (sub-section C.X); and 8) compensation schemes via personal income tax (PIT) reductions (sub-section C.XI).
- **D: Outputs for charts.** This section extracts results for the various charts available in the Dashboard. It comprises of: 1) various chart labels (sub-section D.I); 2) vertical (between-decile) consumption incidence results expressed in “relative terms”/percent of household consumption (sub-section D.II); 3) vertical (between-decile) incidence results expressed in “absolute terms”/local currency units (LCU) (sub-section D.III); 4) horizontal (within-decile) incidence results expressed in “relative terms”/percent of household consumption (sub-section D.IV); 5) percent of climate policy revenues needed to fully compensate given deciles (sub-section D.V); and 6) percent increases in industry/firm costs by sector (sub-section D.VI). This area should remain ‘ungrouped’ (or otherwise unhidden), to allow for visualization of the relevant charts in the Dashboard.

1.3.4.3 The Air pollution tab

The Air pollution module is divided into several sub-sections, as presented in Figure 1.45.

- **Part A: Description or Overview.** The first part of the module contains an overview of the contents in the tab. This tab receives as input energy consumption and emissions from the Mitigation module. Using those inputs (among other inputs), this module produces ambient concentrations of fine particulate matter and ozone, health impacts and economic impacts of pollution.
- **Part B: Key assumptions and inputs.** This section contains all the calibration options available for the air pollution module, inputs from the Mitigation module, and other inputs required for calculations. In general, in this section are included calculations that will feed both the baseline and carbon tax calculations, such as the health effects relative risk functions, baseline incidence rates, value of the statistical life, among others (see Figure 1.45a).
- **Part C: Baseline.** This section contains all the calculations for the baseline scenario, including ambient concentrations of PM2.5 and O3, relative risks, population exposed to

	A	B	C	D		A	B	C	D
1		Submodule	Variable 1	Variable 2	1402	C Baseline			
2	A Air Pollution Module - Malaysia				1403	Modeled concentrations of PM2.5			
3	Description				1860				
8					1861	Modeled concentrations of Ozone			
9	B Key assumptions and inputs				2019				
10	List of abbreviations and units				2020	Total concentration of PM2.5 and O3			
25					2131				
26	Calibration options from the Dashboard/MSTInputs tab				2132	RR Outdoors Air Pollution			
47					2220				
48	Other assumptions and advanced calibration options				2221	RR Outdoors Air Pollution + Household Air Pollution			
99					2309				
100	Energy consumption (from Mitigation tab)				2310	RR Ozone			
140					2315				
141	Emissions (from Mitigation tab)				2316	RR depressive disorders			
617					2320				
618	Exposure to pollution				2321	Population exposed to air pollution			
643					2344				
644	Population distribution				2345	Attributable Burden - OAP - Population NOT exposed to HAP			
704					2426				
705	Emissions to concentrations				2427	Attributable Burden - OAP - Population EXPOSED to HAP			
937					2513				
938	Relative risk functions, GBD 2019				2514	Attributable Burden - OAP - Total			
995					2547				
996	Baseline incidence rates				2548	Attributable Burden - HAP			
1026					2672				
1027	Total deaths, YLL and YLD				2673	Multiple risks factors cop, 25 +			
1129					2684				
1130	Incidence rates for the Minimum Risk Exposure Level				2685	Attributable Burden - Depressive disorders			
1184					2700				
1185	Value of the statistical life (VSL) and averted mortality distribution				2701	Attributable Burden - Ozone cop			
1261					2734				
1262	Productivity and market output				2735	Health expenditure			
1344					2739				
1345	Working days lost				2740	Working days lost			
1367					2747				
1368	Health expenditure				2748	Marginal change in global temperature, compared to 2018			
1395					2756				
1396	Revenues (from Mitigation)				2757	D Carbon tax			
					2758	Modeled concentrations of PM2.5			
					3215				
					3216	Modeled concentrations of Ozone			
					3374				

(a) Sections A and B in the Air pollution tab

(b) Sections C and D in the Air pollution tab

Figure 1.45: Overview of the Air Pollution tab in CPAT

pollution, the attributable burden of pollution (mortality and morbidity) and working days lost due to pollution.

- **Part D: Carbon price policy.** This section contains all the calculations for the policy scenario selected in the Dashboard tab. Sections D and C have the exact same calculations. As in the Mitigation tab, section C can be copy-pasted into section C.
- **Part E: Results for other modules.** The Road Transport module in CPAT uses some of the calculations made in the Air pollution module, such as daily earning from workers, the value of the Statistical life and population above 15 years old. Those variables are in this section.
- **Part F: Results for charts.** In this section are located some additional calculations regarding the difference between metrics in the baseline and in the carbon price scenarios. All the graphs included in the Dashboard, related to the Air pollution module, are feed by data from this section.
- **Part G: Equations and notes.** This section includes some of the equations used inside the air pollution module. They are numbered and when they are used inside the module, they are referenced using the equation number.

G Equations and notes			Go back up	
Equation 1	$ProportionHH_{carbon\ price} = ProportionHH_{baseline} * (1 + Leakage * F_{prop_HH})$		Eq1_Baseline	Eq1_Scenario
Equation 2	$F_{prop_HH_{adjusted}} = \left(\frac{MaxPropHH}{ProportionHH_{baseline}} - 1 \right) * \frac{1}{Leakage}$		Eq2_Baseline	Eq2_Scenario
Equation 3	$F_{prop_HH} = \begin{cases} \text{if } ProportionHH_{carbon\ price} > Max \text{ then } F_{prop_HH_{adjusted}} \\ \text{else } ProportionHH_{carbon\ price} \end{cases}$		Eq3_Baseline	Eq3_Scenario
Equation 4	$\sum_{k=m}^n a^k = \sum_{k=0}^n a^k - \sum_{k=0}^m a^k = \frac{1 - a^{n+1}}{1 - a} - \frac{1 - a^{m+1}}{1 - a}$			
Equation 5	$\frac{PV_{25-29}}{W} = \pi_{25,29} * \sum_{k=0}^2 a^k + \pi_{25,34} * \sum_{k=3}^7 a^k + \dots + \pi_{25,64} * \sum_{k=43}^{47} a^k$			
Equation 6	Machine learning model. Concentration as a funtion of emissions perturbations, P			
	Concentration (P) =	$\begin{cases} \text{if } P < -100, & a_{-100} \\ \text{if } -100 \leq P < -80, & a_{-100} + b_{-100} * (P - -100) \\ \text{if } -80 \leq P < -60, & a_{-80} + b_{-80} * (P - -80) \\ \text{if } -60 \leq P < -40, & a_{-60} + b_{-60} * (P - -60) \\ \text{if } -40 \leq P < -20, & a_{-40} + b_{-40} * (P - -40) \\ \text{if } -20 \leq P < 0, & a_{-20} + b_{-20} * (P - -20) \\ \text{if } 0 \leq P < 20, & a_0 + b_0 * (P - 0) \\ \text{if } 20 \leq P < 40, & a_{20} + b_{20} * (P - 20) \\ \text{if } 40 \leq P < 60, & a_{40} + b_{40} * (P - 40) \\ \text{if } 60 \leq P < 80, & a_{60} + b_{60} * (P - 60) \\ \text{if } 80 \leq P < 100, & a_{80} + b_{80} * (P - 80) \\ \text{if } P > 100, & a_{100} + b_{100} * (P - 100) \end{cases}$		

Figure 1.46: Part G, Air Pollution module in CPAT

1.3.4.4 The Transport tab

The Transport tab includes the road transport modelling for CPAT. The module is divided into several sub-sections, following a similar structure than the other CPAT modules, as presented in Figure 1.47.

- **Part A: Description.** The first part of the module contains an overview of the contents in the tab. This tab receives as input the changes in fuel prices from the Mitigation

B KEY ASSUMPTIONS AND INPUTS	
. Key assumptions	
. Elasticities	
. Country-specific characteristics	
C Baseline	1
Road fuel prices	
Vehicle-kilometers traveled	
Accidents	
Congestion	
Road damage	
Travel time	
D - Carbon tax	2
Road fuel prices	
Mitigation	Air pollution
Distribution	Transport
DATA_MITIGATION->	MTInputs
MTOutputs	GHGs
Prices_dom	Pric

Figure 1.47: Overview of the Transport tab in CPAT

module. Using those inputs (among other inputs), this module produces the number of fatalities from road accidents, additional travel time due to congestion and road damages.

- **Part B: Key assumptions and inputs.** This section contains all the calibration options available for the Road Transport module, country characteristics and elasticities.
- **Part C: Baseline.** This section contains all the calculations for the baseline scenario (accidents, travel time, road damage, among others) and fuel prices for the baseline, from the Mitigation tab.
- **Part D: Carbon price policy.** This section contains all the calculations for the policy scenario (accidents, travel time, road damage, among others) and fuel prices for the policy scenario, from the Mitigation tab. Sections D and C have the exact same calculations. As in the Mitigation tab, section C can be copy-pasted into section C.
- **Part E: Results for other modules.** In this section are results from the Road Transport module that will be used in other modules. For instance, the welfare metrics calculated in the Mitigation module are using the transport externalities from this section.
- **Part F: Results for charts.** In this section are located some additional calculations regarding the difference between metrics in the baseline and in the carbon price scenarios. All the graphs included in the Dashboard related to the Road Transport module using the metrics in this section.

1.3.4.5 Data sources tab

CPAT data sources and terms and conditions are shown here in the Data sources tab.

CPAT Data Sources Terms & Conditions				
This tab lists the terms and conditions for data sources - by using this tool you are agreeing to the terms & conditions below. Modules use raw or refined data from several sources, indicated below.				
CPAT module	CPAT data tabs:	Data category:	Data source:	Link to data or Terms and Conditions (as applicable)
Mitigation	GHGs	Open	UNFCCC & WRI CAIT	WRI CAIT: https://www.wri.org/our-work/project/cait-climate-data-explorer UNFCCC: https://unfccc.int/process-and-meetings/transparency-and-reporting/greenhouse-gas-data/ghg-data-unfccc/ghg-data-from-unfccc
Mitigation	NDCs	Open	Climate Watch	https://www.climatewatchdata.org/ndcs-explore
Mitigation	Prices	Derivatives from proprietary data	Various: IEA, Enerdata country offices, OECD. Refined.	IEA: https://iea.blob.core.windows.net/assets/3bf6ce57-3df6-4639-bf60-d73ee8f017c0/IEA-Terms-April-2020.pdf Enerdata: https://www.enerdata.net/terms-conditions.html OECD: https://www.oecd.org/termsandconditions/?_ga=2.92732957.129827420.1622686486-574055691.1595441182
Mitigation	Elasticities	Open	Various (literature review)	N/A
Mitigation	ECPPC	Open	WB Carbon Pricing Dashboard	https://carbonpricingdashboard.worldbank.org/
Mitigation	Power	Derivatives from open data	CPAT calculations	N/A
Mitigation	SCC	Open	Ricke, K., L. Drouet, K. Caldeira and I	https://www.nature.com/articles/s41558-018-0282-y
Mitigation	WDI	Open	World Development Indicators	https://databank.worldbank.org/source/world-developpr
Mitigation	WEO2019	Open	IMF WEO	https://www.imf.org/en/Publications/SPROLLS/world-e
Mitigation	WEO2020	Open	IMF WEO	https://www.imf.org/en/Publications/SPROLLS/world-e
Mitigation	WEOBOP	Open	IMF WEO	https://www.imf.org/en/Publications/SPROLLS/world-e
Mitigation	Energy_intprice	Open	World Bank Commodity Price Forecasts, IMF World Economic Outlook, IEA World Energy Outlook	WB: https://www.worldbank.org/en/research/commodity-markets ; IMF: https://www.imf.org/en/Publications/WEO IEA: https://www.iea.org/topics/world-energy-outlook EIA: https://www.eia.gov/outlooks/aeo/tables_ref.php

Figure 1.48: CPAT datasources and T&Cs

1.3.4.6 MTInputs tab

This tab contains the assumptions and parameters that are used in the calculations in CPAT. This means that the configuration observed in the Dashboard (explained in this document) is not directly used in the calculations. Rather, the settings from this tab, MTInputs, are used depending on the CPAT running mode. CPAT can be run in three different modes:

1. It can be run ‘from the dashboard’ with user selected settings.
2. It can be run using fully default settings. To change this, please see element 4 in the main policy input area and select ‘Defaults’.
3. It can be run in multi-country, multi-policy mode. To select this, use the ‘Multiscenario Tool’, described in section 1.3.5, which is a separate spreadsheet.

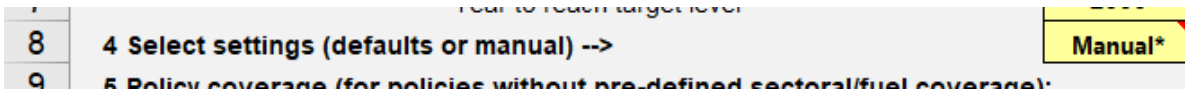


Figure 1.49: Set Default Settings

All of these three sets of parameters ‘flow through’ MTinputs tab, which shows the comprehensive parameter set used for calculation in CPAT.

Parameters	unit	MT values	"Dashboard" values	Used for calculation	Defaults	NameOfParameter
Scenario Identification						
Country		0	China	China	China	Countryname
Scenario ID	#	0	N/A	N/A	N/A	
Scenario status	switch	0	N/A	N/A	N/A	
Scenario name	name	0	N/A	N/A	N/A	
Chosen policy	switch	0	- Carbon tax	- Carbon tax	- Carbon tax	ScenarioSelected
Scenario status for macro	#	0	N/A	N/A	N/A	
Scenario parameters override?	#	0	N/A	N/A	N/A	
CPAT-side parameters override?	switch	0	Manual*	Manual*	Manual*	CPATDefaultsOrUserDefined
Carbon pricing: main inputs						
Carbon pricing start year	year	0	2022	2022	2022	CP_Intro
Starting carbon price	nom. USD/ACO2	0	0	0	0	CP_LevelStart
Target level of carbon price	nom. USD/ACO2	0	0	0	0	CP_LevelTarget
Year to reach target level	year	0	2030	2030	2030	CP_Outro

Figure 1.50: MTInputs: Comprehensive Parameter Inputs

1.3.4.7 MTOutputs tab

As it was explained in the previous section, CPAT can be run in a “multi-country, multi-policy” mode. When this is the case, the tab MTOutputs stores the results that will be exported to the Multiscenario Tool, described in the following section. This tab contains a series of indicators, reflecting the main results from each CPAT module. A view of this tab is presented in the next figure.

CPAT OUTPUTS FOR MT						
Explanation: this tab copies CPAT outputs for MT. Do not change						
IMPORTANT: Please check the static data in columns BW and right. Easier to do this if columns G-BV are temporarily hidden						
Include?	Country	Scenario	CPATIndicator	CPATCode	MTCode	RCode
Policy characteristics						
Yes	Chile	N/A	Emissions coverage	chl.mit.co2cov.2	N/A	chl.mit.co2cov_
Yes	Chile	N/A	Carbon tax trajectory	chl.mit.cptraj.2	N/A	chl.mit.cptraj_a
Yes	Chile	N/A	Effective carbon tax trajectory	chl.mit.effcptraj.2	N/A	chl.mit.effcptraj
Yes	Chile	N/A	Emissions covered by sector: power sector	chl.mit.co2cov.pow.cont.2	N/A	chl.mit.co2cov_
Yes	Chile	N/A	Emissions covered, transport sector	chl.mit.co2cov tra.cont.2	N/A	chl.mit.co2cov_
Yes	Chile	N/A	Emissions covered, residential sector	chl.mit.co2cov.res.cont.2	N/A	chl.mit.co2cov_
Yes	Chile	N/A	Emissions covered, industry	chl.mit.co2cov.ind.cont.2	N/A	chl.mit.co2cov_
Yes	Chile	N/A	Emissions covered, other energy use	chl.mit.co2cov.oth.cont.2	N/A	chl.mit.co2cov_
Macro effects						

Figure 1.51: MTOutputs: Code-readable Output tab

1.3.5 The Multiscenario Tool (MT)

CPAT run in standalone mode relates to a single country with two scenarios: the baseline and a policy scenario. CPAT can also be run in multiscenario mode, meaning for many countries and/or many scenarios. More information about the multiscenario tool is available on request.

Figure 1.52: The Multiscenario Tool

1.4 Country coverage

CPAT currently covers 192 countries. The table below presents the list of countries and indicates whether the country is covered by CPAT (with ‘Y’ = Yes, indicating the country being covered by CPAT). If the country is not covered, an explanation is provided to detail what are the missing information.

Country code	Income Group	Country	Region	Coverage	Distribution
AFG	LIC	Afghanistan	South Asia	Y	
ALB	UMIC	Albania	Europe & Central Asia	Y	
DZA	UMIC	Algeria	Middle East & North Africa	Y	
ASM	UMIC	American Samoa	East Asia & Pacific	Y	
AND	HIC	Andorra	Europe & Central Asia	Macro data not available (employment; emissions data)	
AGO	LMIC	Angola	Sub-Saharan Africa	Y	
AIA	UMIC	Anguilla	Latin America & Caribbean	Spurious results’ lack of energy consumption data	
ATG	HIC	Antigua and Barbuda	Latin America & Caribbean	Y	
ARG	HIC	Argentina	Latin America & Caribbean	Y	Y

Country code	Income Group	Country	Region	Coverage	Distribution
ARM	UMIC	Armenia	Europe & Central Asia	Y	
ABW	HIC	Aruba	Latin America & Caribbean	Y	
AUS	HIC	Australia	East Asia & Pacific	Y	
AUT	HIC	Austria	Europe & Central Asia	Y	Y
AZE	UMIC	Azerbaijan	Europe & Central Asia	Y	
BHS	HIC	Bahamas, The	Latin America & Caribbean	Y	
BHR	HIC	Bahrain	Middle East & North Africa	Y	
BGD	LMIC	Bangladesh	South Asia	Y	Y
BRB	HIC	Barbados	Latin America & Caribbean	Y	
BLR	UMIC	Belarus	Europe & Central Asia	Y	

Country code	Income Group	Country	Region	Coverage	Distribution
BEL	HIC	Belgium	Europe & Central Asia	Y	Y
BLZ	UMIC	Belize	Latin America & Caribbean	Y	
BEN	LIC	Benin	Sub- Saharan Africa	Y	
BMU	HIC	Bermuda	North America	Macro data not available (GDP per capita - real (constant prices); employment)	
BTN	LMIC	Bhutan	South Asia	Y	
BOL	LMIC	Bolivia	Latin America & Caribbean	Y	Y
BIH	UMIC	Bosnia and Herzegov- ina	Europe & Central Asia	Y	
BWA	UMIC	Botswana	Sub- Saharan Africa	Y	
BRA	UMIC	Brazil	Latin America & Caribbean	Y	Y
VGB	HIC	British Virgin Islands	Latin America & Caribbean	Macro data not available (GDP indicators, employment and population, exchange rate)	
BRN	HIC	Brunei Darus- salam	East Asia & Pacific	Y	

Country code	Income Group	Country	Region	Coverage	Distribution
BGR	UMIC	Bulgaria	Europe & Central Asia	Y	Y
BFA	LIC	Burkina Faso	Sub- Saharan Africa	Y	
BDI	LIC	Burundi	Sub- Saharan Africa	Y	
CPV	LMIC	Cabo Verde	Sub- Saharan Africa	Y	
KHM	LMIC	Cambodia	East Asia & Pacific	Y	
CMR	LMIC	Cameroon	Sub- Saharan Africa	Y	
CAN	HIC	Canada	North America	Y	Y
CYM	HIC	Cayman Islands	Latin America & Caribbean	Y	
CAF	LIC	Central African Republic	Sub- Saharan Africa	Y	
TCD	LIC	Chad	Sub- Saharan Africa	Y	
CHI	HIC	Channel Islands	Europe & Central Asia	Macro data not available (GDP indicators, employment, population, emissions); problem with externalities.	
CHL	HIC	Chile	Latin America & Caribbean	Y	Y

Country code	Income Group	Country	Region	Coverage	Distribution
CHN	UMIC	China	East Asia & Pacific	Y	Y
COL	UMIC	Colombia	Latin America & Caribbean	Y	Y
COM	LIC	Comoros	Sub- Saharan Africa	Y	
COD	LIC	Congo, Demo- cratic Republic of the	Sub- Saharan Africa	Y	
COG	LMIC	Congo, Republic of	Sub- Saharan Africa	Y	
CRI	UMIC	Costa Rica	Latin America & Caribbean	Y	Y
CIV	LMIC	Côte d'Ivoire	Sub- Saharan Africa	Y	Y
HRV	HIC	Croatia	Europe & Central Asia	Y	Y
CUB	UMIC	Cuba	Latin America & Caribbean	Y	
CUW	HIC	Curaçao	Latin America & Caribbean	Macro data not available (employment, GDP per capita - real (constant prices), problem with externalities; spurious results' balances issues).	

Country code	Income Group	Country	Region	Coverage	Distribution
CYP	HIC	Cyprus	Europe & Central Asia	Y	Y
CZE	HIC	Czech Republic	Europe & Central Asia	Y	Y
DNK	HIC	Denmark	Europe & Central Asia	Y	Y
DJI	LMIC	Djibouti	Middle East & North Africa	Y	
DMA	UMIC	Dominica	Latin America & Caribbean	Y	
DOM	UMIC	Dominican Republic	Latin America & Caribbean	Y	Y
ECU	UMIC	Ecuador	Latin America & Caribbean	Y	Y
EGY	LMIC	Egypt	Middle East & North Africa	Y	Y
SLV	LMIC	El Salvador	Latin America & Caribbean	Y	
GNQ	UMIC	Equatorial Guinea	Sub- Saharan Africa	Y	

Country code	Income Group	Country	Region	Coverage	Distribution
ERI	LIC	Eritrea	Sub-Saharan Africa	Y	
EST	HIC	Estonia	Europe & Central Asia	Y	Y
SWZ	LMIC	Eswatini	Sub-Saharan Africa	Macro data not available (employment, GDP per capita - real (constant prices); problem with externalities).	
ETH	LIC	Ethiopia	Sub-Saharan Africa	Y	
FRO	HIC	Faroe Islands	Europe & Central Asia	Macro data not available (GDP indicators, employment); missing externalities; spurious results' balances issues.	
FJI	UMIC	Fiji	East Asia & Pacific	Y	
FIN	HIC	Finland	Europe & Central Asia	Y	Y
FRA	HIC	France	Europe & Central Asia	Y	Y
PYF	HIC	French Polynesia	East Asia & Pacific	Macro data not available (employment, GDP per capita - real (constant prices); problem with externalities).	
GAB	UMIC	Gabon	Sub-Saharan Africa	Y	
GMB	LIC	Gambia, The	Sub-Saharan Africa	Y	

Country code	Income Group	Country	Region	Coverage	Distribution
GEO	LMIC	Georgia	Europe & Central Asia	Y	
DEU	HIC	Germany	Europe & Central Asia	Y	Y
GHA	LMIC	Ghana	Sub-Saharan Africa	Y	Y
GIB	HIC	Gibraltar	Europe & Central Asia	Macro data not available (GDP indicators, employment, population); problem with externalities).	
GRC	HIC	Greece	Europe & Central Asia	Y	Y
GRL	HIC	Greenland	Europe & Central Asia	Y	
GRD	UMIC	Grenada	Latin America & Caribbean	Y	
GUM	HIC	Guam	East Asia & Pacific	Macro data not available (employment, GDP per capita - real (constant prices); problem with externalities).	
GTM	UMIC	Guatemala	Latin America & Caribbean	Y	
GIN	LIC	Guinea	Sub-Saharan Africa	Y	
GNB	LIC	Guinea-Bissau	Sub-Saharan Africa	Y	

Country code	Income Group	Country	Region	Coverage	Distribution
GUY	UMIC	Guyana	Latin America & Caribbean	Y	
HTI	LIC	Haiti	Latin America & Caribbean	Y	
HND	LMIC	Honduras	Latin America & Caribbean	Y	Y
HKG	HIC	Hong Kong SAR	East Asia & Pacific	Y	
HUN	HIC	Hungary	Europe & Central Asia	Y	Y
ISL	HIC	Iceland	Europe & Central Asia	Y	
IND	LMIC	India	South Asia	Y	Y
IDN	LMIC	Indonesia	East Asia & Pacific	Y	Y
IRN	UMIC	Iran	Middle East & North Africa	Y	
IRQ	UMIC	Iraq	Middle East & North Africa	Y	
IRL	HIC	Ireland	Europe & Central Asia	Y	Y

Country code	Income Group	Country	Region	Coverage	Distribution
IMN	HIC	Isle of Man	Europe & Central Asia	Macro data not available (employment, GDP per capita - real (constant prices), emissions; problem with externalities).	
ISR	HIC	Israel	Middle East & North Africa	Y	
ITA	HIC	Italy	Europe & Central Asia	Y	Y
JAM	UMIC	Jamaica	Latin America & Caribbean	Y	
JPN	HIC	Japan	East Asia & Pacific	Y	
JOR	UMIC	Jordan	Middle East & North Africa	Y	
KAZ	UMIC	Kazakhstan	Europe & Central Asia	Y	Y
KEN	LMIC	Kenya	Sub- Saharan Africa	Y	
KIR	LMIC	Kiribati	East Asia & Pacific	Y	
KOR	HIC	Korea	East Asia & Pacific	Y	
PRK	LIC	Korea, Dem. People's Rep.	East Asia & Pacific	Macro data not available (GDP indicators, employment); missing externalities.	

Country code	Income Group	Country	Region	Coverage	Distribution
XKX	LMIC	Kosovo	Europe & Central Asia	Data not available (Historical CO2 & other GHGs emissions).	
KWT	HIC	Kuwait	Middle East & North Africa	Y	
KGZ	LMIC	Kyrgyz Republic	Europe & Central Asia	Y	
LAO	LMIC	Lao P.D.R.	East Asia & Pacific	Y	
LVA	HIC	Latvia	Europe & Central Asia	Y	Y
LBN	UMIC	Lebanon	Middle East & North Africa	Y	
LSO	LMIC	Lesotho	Sub- Saharan Africa	Y	
LBR	LIC	Liberia	Sub- Saharan Africa	Y	
LBY	UMIC	Libya	Middle East & North Africa	Y	
LIE	HIC	Liechtenstein	Europe & Central Asia	Macro data not available (GDP indicators, employment); missing externalities.	

Country code	Income Group	Country	Region	Coverage	Distribution
LTU	HIC	Lithuania	Europe & Central Asia	Y	Y
LUX	HIC	Luxembourg	Europe & Central Asia	Y	Y
MAC	HIC	Macao SAR	East Asia & Pacific	Y	
MKD	UMIC	Macedonia, FYR	Europe & Central Asia	Y	Y
MDG	LIC	Madagascar	Sub- Saharan Africa	Y	Y
MWI	LIC	Malawi	Sub- Saharan Africa	Y	
MYS	UMIC	Malaysia	East Asia & Pacific	Y	Y
MDV	UMIC	Maldives	South Asia	Y	
MLI	LIC	Mali	Sub- Saharan Africa	Y	Y
MLT	HIC	Malta	Middle East & North Africa	Y	Y
MHL	UMIC	Marshall Islands	East Asia & Pacific	Data not available (Historical CO2 & other GHGs emissions).	
MRT	LMIC	Mauritania	Sub- Saharan Africa	Y	

Country code	Income Group	Country	Region	Coverage	Distribution
MUS	UMIC	Mauritius	Sub- Saharan Africa	Y	
MEX	UMIC	Mexico	Latin America & Caribbean	Y	Y
FSM	LMIC	Micronesia	East Asia & Pacific	Y	
MDA	LMIC	Moldova	Europe & Central Asia	Y	
MCO	HIC	Monaco	Europe & Central Asia	Macro data not available (employment, GDP per capita - real (constant prices); problem with air pollution externalities).	
MNG	LMIC	Mongolia	East Asia & Pacific	Y	
MNE	UMIC	Montenegro, Rep. of	Europe & Central Asia	Data not available (Historical CO2 & other GHGs emissions).	
MSR	UMIC	Montserrat	Latin America & Caribbean	Data not available (Historical CO2 & other GHGs emissions).	
MAR	LMIC	Morocco	Middle East & North Africa	Y	
MOZ	LIC	Mozambique	Sub- Saharan Africa	Y	
MMR	LMIC	Myanmar	East Asia & Pacific	Y	

Country code	Income Group	Country	Region	Coverage	Distribution
NAM	UMIC	Namibia	Sub- Saharan Africa	Y	
NRU	UMIC	Nauru	East Asia & Pacific	Y	
NPL	LIC	Nepal	South Asia	Y	Y
NLD	HIC	Netherlands	Europe & Central Asia	Y	Y
NCL	HIC	New Caledonia	East Asia & Pacific	Macro data not available (GDP indicators, employment); problem with externalities.	
NZL	HIC	New Zealand	East Asia & Pacific	Y	
NIC	LMIC	Nicaragua	Latin America & Caribbean	Y	
NER	LIC	Niger	Sub- Saharan Africa	Y	
NGA	LMIC	Nigeria	Sub- Saharan Africa	Y	
MNP	HIC	Northern Mariana Islands	East Asia & Pacific	Macro data not available (employment, GDP per capita - real (constant prices); problem with externalities; balances issues).	
NOR	HIC	Norway	Europe & Central Asia	Y	
OMN	HIC	Oman	Middle East & North Africa	Y	

Country code	Income Group	Country	Region	Coverage	Distribution
PAK	LMIC	Pakistan	South Asia	Y	Y
PLW	HIC	Palau	East Asia & Pacific	Y	
PAN	HIC	Panama	Latin America & Caribbean	Y	
PNG	LMIC	Papua New Guinea	East Asia & Pacific	Y	
PRY	UMIC	Paraguay	Latin America & Caribbean	Y	
PER	UMIC	Peru	Latin America & Caribbean	Y	Y
PHL	LMIC	Philippines	East Asia & Pacific	Y	Y
POL	HIC	Poland	Europe & Central Asia	Y	Y
PRT	HIC	Portugal	Europe & Central Asia	Y	Y
PRI	HIC	Puerto Rico	Latin America & Caribbean	Y	
QAT	HIC	Qatar	Middle East & North Africa	Y	

Country code	Income Group	Country	Region	Coverage	Distribution
ROU	UMIC	Romania	Europe & Central Asia	Y	Y
RUS	UMIC	Russia	Europe & Central Asia	Y	
RWA	LIC	Rwanda	Sub- Saharan Africa	Y	Y
WSM	UMIC	Samoa	East Asia & Pacific	Y	
SMR	HIC	San Marino	Europe & Central Asia	Data not available (Historical CO2 & other GHGs emissions); Spurious results' balances issues.	
STP	LMIC	São Tomé and Príncipe	Sub- Saharan Africa	Y	
SAU	HIC	Saudi Arabia	Middle East & North Africa	Y	
SEN	LIC	Senegal	Sub- Saharan Africa	Y	
SRB	UMIC	Serbia	Europe & Central Asia	Y	Y
SYC	HIC	Seychelles	Sub- Saharan Africa	Y	
SLE	LIC	Sierra Leone	Sub- Saharan Africa	Y	

Country code	Income Group	Country	Region	Coverage	Distribution
SGP	HIC	Singapore	East Asia & Pacific	Y	
SXM	HIC	Sint Maarten (Dutch part)	Latin America & Caribbean	Macro data not available (employment, GDP per capita - real (constant prices); historical CO2 & other GHGs emissions; problem with balances).	
SVK	HIC	Slovak Republic	Europe & Central Asia	Y	Y
SVN	HIC	Slovenia	Europe & Central Asia	Y	Y
SLB	LMIC	Solomon Islands	East Asia & Pacific	Y	
SOM	LIC	Somalia	Sub- Saharan Africa	Y	
ZAF	UMIC	South Africa	Sub- Saharan Africa	Y	
SSD	LIC	South Sudan	Sub- Saharan Africa	Data not available (Historical CO2 & other GHGs emissions); Spurious results' balances issues.	
ESP	HIC	Spain	Europe & Central Asia	Y	Y
LKA	LMIC	Sri Lanka	South Asia	Y	Y
KNA	HIC	St. Kitts and Nevis	Latin America & Caribbean	Y	

Country code	Income Group	Country	Region	Coverage	Distribution
LCA	UMIC	St. Lucia	Latin America & Caribbean	Y	
MAF	HIC	St. Martin (French part)	Latin America & Caribbean	Macro data not available (GDP indicators, employment); historical CO2 & other GHGs emissions; problem with externalities.	
VCT	UMIC	St. Vincent and the Grenadines	Latin America & Caribbean	Y	
SDN	LMIC	Sudan	Sub- Saharan Africa	Y	
SUR	UMIC	Suriname	Latin America & Caribbean	Y	
SWE	HIC	Sweden	Europe & Central Asia	Y	Y
CHE	HIC	Switzerland	Europe & Central Asia	Y	
SYR	LIC	Syria	Middle East & North Africa	Macro data not available (GDP indicators, employment); problem with externalities.	
TWN	HIC	Taiwan Province of China	East Asia & Pacific	Y	
TJK	LIC	Tajikistan	Europe & Central Asia	Y	

Country code	Income Group	Country	Region	Coverage	Distribution
TZA	LIC	Tanzania	Sub- Saharan Africa	Y	
THA	UMIC	Thailand	East Asia & Pacific	Y	Y
TLS	LMIC	Timor- Leste	East Asia & Pacific	Y	
TGO	LIC	Togo	Sub- Saharan Africa	Y	
TON	UMIC	Tonga	East Asia & Pacific	Y	
TTO	HIC	Trinidad and Tobago	Latin America & Caribbean	Y	
TUN	LMIC	Tunisia	Middle East & North Africa	Y	
TUR	UMIC	Turkey	Europe & Central Asia	Y	Y
TKM	UMIC	Turkmenistan	Europe & Central Asia	Y	
TCA	HIC	Turks and Caicos Islands	Latin America & Caribbean	Y	
TUV	UMIC	Tuvalu	East Asia & Pacific	Spurious results' balances issues, missing historical CO2 & other GHGs emissions data.	

Country code	Income Group	Country	Region	Coverage	Distribution
UGA	LIC	Uganda	Sub- Saharan Africa	Y	
UKR	LMIC	Ukraine	Europe & Central Asia	Y	Y
ARE	HIC	United Arab Emirates	Middle East & North Africa	Y	
GBR	HIC	United Kingdom	Europe & Central Asia	Y	Y
USA	HIC	United States	North America	Y	Y
URY	HIC	Uruguay	Latin America & Caribbean	Y	Y
UZB	LMIC	Uzbekistan	Europe & Central Asia	Y	
VUT	LMIC	Vanuatu	East Asia & Pacific	Y	
VEN	UMIC	Venezuela	Latin America & Caribbean	Macro data not available (GDP indicators)	
VNM	LMIC	Vietnam	East Asia & Pacific	Y	Y
VIR	HIC	Virgin Islands (U.S.)	Latin America & Caribbean	Macro data not available (employment, GDP per capita - real (constant prices); problem with externalities, balances issues).	

Country code	Income Group	Country	Region	Coverage	Distribution
PSE	LMIC	West Bank and Gaza	Middle East & North Africa	Macro data not available (employment, GDP per capita - real (constant prices); missing historical CO2 & other GHGs emissions data).	
YEM	LIC	Yemen	Middle East & North Africa	Y	
ZMB	LMIC	Zambia	Sub-Saharan Africa	Y	
ZWE	LIC	Zimbabwe	Sub-Saharan Africa	Y	
WORLD	AV	World aviation bunkers	World aviation bunkers	Y	
WORLD	MA	World marine bunkers	World marine bunkers	Y	

1.5 Parameters in CPAT

When opening CPAT, the tool will be already configured using a set of assumptions and parameter values. The following table shows the initial or default configuration in CPAT. Notice that an asterisk represents the recommended default values, that the user can select if unsure about the best assumption to use for a particular country and context.

Explanation

Code Name

Default

Carbon pricing: main inputs

Carbon pricing start year

CPIntro

2023

Starting carbon price

CPLevelStart

25

Target level of carbon price

CPLevelTarget

75

Year to reach target level

CPOutro

2030

Carbon pricing: fuel coverage

Apply tax to coal?

MCovCoa

TRUE

Apply tax to natural gas?

MCovNga

TRUE

Apply tax to gasoline?

MCovGso

TRUE

Apply tax to diesel?

MCovDie

TRUE

Apply tax to LPG?

MCovLpg

TRUE

Apply tax to kerosene?

MCovKer

TRUE

Apply tax to non-road oil products?

MCovOop

TRUE

Carbon pricing: sector coverage

Apply tax to power sector?

MCovPow

TRUE

Apply tax to road transportation?

MCovRod

TRUE

Apply tax to rail transportation?

MCovRal

TRUE

Apply tax to domestic aviation?

MCovAvi

TRUE

Apply tax to domestic shipping?

MCovNav

TRUE

Apply tax to residential sector?

MCovRes

TRUE

Apply tax to food & forestry?

MCovFoo

TRUE

Apply tax to services (private / public)?

MCovSrv

TRUE

Apply tax to mining & chemicals?

MCovMch

TRUE

Apply tax to iron and steel?

MCovIrn

TRUE

Apply tax to non-ferrous metals?

MCovNfm

TRUE

Apply tax to machinery?

MCovMac

TRUE

Apply tax to cement?

MCovCem

TRUE

Apply tax to other manufacturing?

MCovOmn

TRUE

Apply tax to construction?

MCovCst

TRUE

Apply tax to fuel transformation?

MCovFtr

TRUE

Apply tax to other energy use?

MCovOen

TRUE

Exemptions phaseout

Apply exemption phaseout?

ExemptPhaseout

TRUE

Year to start exemption phaseout (if applicable)

YearPha

2023

Period to reach full exemption phaseout (if applicable)

ExemptPhaseoutPeriod

5

Fossil fuel subsidies (producer-side)

Apply producer subsidies phaseout in the policy scenario?

ProdSubPh

FALSE

Year to start producer subsidies phaseout (if applicable)

YearProdSubPha

2023

Period to reach full producer subsidies phaseout (if applicable)

FFSProdPhaseoutPeriod

5

Share of producer subsidies to phase-out

ShareofProdSubPha

1

Apply producer subsidies phaseout in the baseline?

ProdSubPhaBaseline

No

Period to reach full producer subsidies phaseout (baseline)

FFSProdPhaseoutPeriodBA

5

Share of producer subsidies to phase-out in the baseline

ShareOfProdSubPhaBA

1

Fossil fuel subsidies (consumer-side)

Apply consumer subsidies phaseout?

ConsSubPha

FALSE

Year to start consumer subsidies phaseout (if applicable)

YearConsSubPha

2023

Period to reach full consumer subsidies phaseout (if applicable)

FFPhaseOut

5

Share of consumer subsidies to phase-out

ShareOfConsSubPha

1

Apply consumer subsidies phaseout in the baseline?

ConsSubPhaBaseline

No

Period to reach full consumer subsidies phaseout (baseline)

FFSConsPhaseoutPeriodBA

5

Share of consumer subsidies to phase-out in the baseline

ShareofConsSubPhaBA

1

Include power subsidies in any phase out?

PowerSubsidyExemptInclude

Include*

Price liberalization

Apply price controls phaseout?

PrcContPha

FALSE

Year to start price controls phaseout (if applicable)

YearPrcContPha

2023

Period to reach full price controls phaseout (if applicable)

PrcControlPhaseout

5

Government energy price controls

GovPriceControls

Bucketed*

Apply price controls phaseout in the baseline scenario?

PrcContPhaBaseline

No

Revenues use

Labor tax reductions

EXPLabortax

40

Corporate taxes

EXPCIT

0

Public investment

EXPCapex

30

Current spending

EXPGoodsandserv

0

Targeted transfers

EXPTransfers

30

of which:

targeted percentile

TargettedPercentile

40

coverage rate

CoverageRate

75

leakage rate

LeakageRate

25

Policy options

Additional mitigation policies in non-energy sectors?

AdditionMitigationPoliciesNonEnergy

Yes*

Apply existing ETS (if exists)?

ExistingETSApply

Yes*

Existing ETS permit price growth per annum (real terms)

ExistingETSGrowth

0

New carbon tax complementary to existing ETS coverage

CTaxComplimentaryToETS

No*

ETS behavioral responses and revenues adjustment

ETSBehavioralAdjustment

0.9

Years to phase in non-climate Pigouvian tax?

AddEfficientTaxesPhaseInYears

5

Apply existing carbon tax (if exists)?

ExistingCTApply

Yes*

Assumed existing carbon tax growth per annum (real terms)

ExistingCTGrowth

0

Add additional excise tax (see 'Manual inputs' tab)?

AdditionalExcise

No*

Add non-climate Pigouvian tax on top?

AddEfficientTaxes

No*

Externalities are part of VAT base for optimal taxes?

ExternalityAddVAT

Yes*

Sources for key inputs

International energy price forecasts

IntEnerPricForeSource

IMF-WB*

Global energy demand scenario

GlobalEnergyDemand

Stated Policies*

GDP growth forecasts

GDPScenario

WEO*

Primary source for price elasticities of demand

ElPrcMainSrc

Simple*

Primary source for income elasticities of demand

ElIncMainSrc

Simple*

CO2 emissions factors

EmissionsFactCO2

IIASA*

Fiscal multipliers

MultipliersSource

Income-grp*

Power sector model (elasticity or engineering)?

PowModelSelected

Average*

NDC submission

NDCs

Latest*

General assumptions

First year of model calculations?

FirstYearCalculations

2019

Nominal results in real terms of which year?

ResultsYear

2021

Use energy balances or (CPAT) energy consumption data

BalancesOrConsumption

Consumption

Generate Matrix of Energy Consumption Projections for Year

EnergyConsumptionsMatrixProjectionsYear

2019

Adjust Annex I country energy-related CO2 EFs to match UNFCCC GHG inventories?

EFsAdjustmentAnnexI

Yes*

Adjust non-Annex I country energy-related CO2 EFs to match CAIT GHG inventories?

EFsAdjustmentNonAnnexI

Yes*

Industrial process emissions scale with industrial CO2 energy emissions?

IndustrialProcessEmissionsScaleEner

Yes*

LULUCF emissions decline at % pa (in absolute value of start year)?

LULUCFAnnualEmissionsDecline

2.50E-02

Additional policy-induced efficiency gains pa by sector:

Power

AdditionalEfficiencyPower

0

Road vehicles

AdditionalEfficiencyRoadVehicle

0

Residential

AdditionalEfficiencyResidential

0

Industrial

AdditionalEfficiencyIndustrial

0

Adjustment to efficiency margins for shadow pricing policies:

Energy efficiency regulations

SPPEffAdjEnergyEfficiencyRegulations

0.7

Vehicle fuel economy

SPPEffAdjVehicleFuelEconomy

0.7

Residential efficiency regulations

SPPEffAdjRes

0.7

Industrial efficiency regulations

SPPEffAdjInd

0.7

Feebates

SPPEffAdjFeebates

1

Residential Substitution Implicit Efficiencies

LPG

ResSubstLPGEff

0.56

Kerosene

ResSubstKerEff

0.45

Biomass

ResSubstBioEff

0.2

NatGas

ResSubstNatGasEff

0.58

Uncertainty adjustments

International energy prices adjustment

IntEnerPricForecastAdjustment

Base*

GDP growth adjustment

GdpAdj

Base*

Price elasticities adjustment

ElastPriceAdjustment

Base*

Income elasticities adjustment

ElastIncAdjustment

Base*

Adjust income elasticities for GDP levels?

IncElAdj

Yes*

Fiscal multipliers adjustment

FmAdj

Base*

Miscellaneous

Price pathway continues to rise after target year?

ExtendCarbonPriceBeyondOutro

Linear*

Tax pathway is in nominal or real terms?

NomorReal

Real*

Include endogenous GDP effects?

GDPEndogenous

Yes*

Residential LPG/kerosene always exempted

AlwaysExemptResLPGKer

No*

National social cost of carbon (NSCC) source

NSCCSource

Target*

Congestion & road damage attributable to fuels

TransExternAttribPortion

0.01

Override dashboard and impose a linear or exponential carbon price trajectory?

CTaxTrajectoryType

Linear*

If overridden and exponential, what is the real escalation rate per year?

CtaxExponentialEscalationRate

0

Social cost of carbon

NSCC discount rate ()

NSCCDiscountRate

2%*

NSCC elasticity of marginal utility ()

NSCCMargUtilofCons

1.5%*

Global social cost of carbon (GSCC) source

GSCCSource

Target*

SCC (both NSCC and GSCC)

SCCRise

0.04

Target-consistent carbon price by 2030 (for 'Target' option)

SCCTargetConsistentCP

75

Energy pricing assumptions

Use manual domestic prices?

DomPrTax

No

Use uniform global assumption for fuel prices (normally 'No')

UseGlobalPrices

No

Year of interest for energy externalities & prices

YearFuelPrices

2025

VAT reform

Apply general VAT rate on residential and transport consumption?

VatRef

No*

Existing non-carbon taxes

Apply existing non-carbon taxes on coal?

ApplyExistingNonCarbonTaxCoa

Yes*

Apply existing non-carbon taxes on natural gas?

ApplyExistingNonCarbonTaxNga

Yes*

Apply existing non-carbon taxes on gasoline?

ApplyExistingNonCarbonTaxGso

Yes*

Apply existing non-carbon taxes on diesel?

ApplyExistingNonCarbonTaxDie

Yes*

Apply existing non-carbon taxes on other oil products?

ApplyExistingNonCarbonTaxOop

Yes*

Apply existing non-carbon taxes on LPG?

ApplyExistingNonCarbonTaxLpg

Yes*

Apply existing non-carbon taxes on kerosene?

ApplyExistingNonCarbonTaxKer

Yes*

Apply existing non-carbon taxes on biomass?

ApplyExistingNonCarbonTaxBio

Yes*

Apply existing non-carbon taxes on electricity?

ApplyExistingNonCarbonTaxEcy

Yes*

Other assumptions: mitigation module

Use 'world' (USA) or country-specific discount factors?

DfSelection

World

Sum all oil products in industrial transformation sector

NonEnergyTransformationMethod

Converted

LPG in residential implicit (cookstove) efficiency

LPGEff

0.56

Kerosene in residential implicit (cookstove) efficiency

KerEff

0.45

Biomass in residential implicit (cookstove) efficiency

BioEff

0.2

Natural gas in residential implicit (cookstove) efficiency

NatGasEff

0.58

Distributional module assumptions

Analysis year for distributional module

YearDistn

2030

Targeted transfer type

TransferType

Cash

Target households below poverty line (2011 PPP\$/day)

TargetBelow

No

Public/infrastructure investment type

PublicInfrastructureInvType

All Infr.

Current spending type

CurrentSpendingType

All Social Protection and Labor

Personal Income Tax (PIT) reduction type

PITReductionType

Personal Allowance

“Targeted Exemption” for bottom XX deciles

DistExcCfDec

4

Replace missing PIT data, grouping by country

MissingDataReplacement

region

Exempt most-used cooking fossil fuel?

ExemptMostCook

No

Exempt cooking fossil fuel for bottom XX deciles:

ExemptCookDeciles

2

Adjust for behavioral & structural change?

InferredDist

Yes

Include decile-specific price elasticities?

PEDs

No

Adjust GTAP-implied CP revenues to CPAT?

ScaleGTAP

Yes

Adjust for deadweight losses?

DWLs

No

Imperfect pass-through?

PassthroughDist

No

Impacts for average, median, p25, or p75?

QuantilesStatistic

mean

Quantiles in LCU?

QuantilesLCU

No

Air pollution module assumptions

Emissions to concentrations, PM2.5

SourceAppSel

Avg. iF and LS FASST*

Emissions to concentrations, Ozone

SourceAppO3

TM5-FASST

Emission factors

EFSel

Average

Include leakage to biomass in residential sector

BiomassLeakage

No

Biomass is a normal good

BiomassNormal

No

VSL source

VSLMethod

Transfer from OECD

VSL (where manual source)

VSLManual

500000

VSL elasticity source

VslElSource

Income group

VSL elasticity (where manual source)

VslEl

1

Discount rate selection

DiscSel

3% (Robinson 2019)

Discount rate (where manual source)

DiscRate

0.03

Other assumptions: air pollution module

Number of working days per month

WorkDays

20

Labor share of GDP, default value

ApLabSh

0.65

Max % of households using solid fuels

ApMaxSs

0.99

Leakage converted into % HH using solid fuels

ApLeakHh

0.5

Apply cessation lag when discounting averted deaths

ApCessLag

Yes

Power Sector

Power Rebate

PowerRebates

No*

Power price: portion of cost change passed-on:

PowerSectorPriceChangePassOn

1

Year of interest for power sector costs

CostBreakdownYear

2030

Estimate economy-wide or sectoral power demand?

ElasticityModel

Economy-wide

k Parameter dispatch

kDispatch

2

k Parameter investment

kInvestment

2

Minimum WACC

MinimumWACC

0.01

Use old or new generation costs in elasticity model?

PowGenCostsOldNew

New*

Hydro retirement rate set to zero

HydroDoesntRetire

Yes

Minimum (post subsidy) generation cost \$/kwh real

MinPostSubsidyPowerPrice

0.01

RE Subsidies

Baseline renewable energy subsidy, \$/kwh nom

RenewableSubsidyBL

0

New renewable energy subsidy, \$/kwh nom

RenSubsidyAddUSDkwh

0

New renewable energy subsidy, phaseout

RenSubsidyAddPhaseoutYrs

10

Apply additional RE subsidy to hydroelectric power?

RenewableSubsidyHydro

No

RE Scale-up limits

Max new investment in coal/gas as a percentage of total generation

MaxNonVREAsPCOfTotalGen

0.05

Max new investment oil/hyd/nucl/ore/bio as a percentage of total generation

MaxNonHydNucOreBioAsPCOfTotalGen

0.02

User-Defined Setting for VRE Max-Scale up (if used)

MaxWindSolarScaleup

0.02

Max renewable scaleup rate setting

MaxScaleUpRateCategory

CtryDefault*

More Power Generation Settings

Use Elasticity Model Power Demand In Engineer Model

UseElasticityModelPowerDemandInEngineerModel

No*

Cost of capital: User-defined, Inc-dep, or Tech-dep?

WACCSource

Income*

If Global, what Value?

WACCUserGlobal

7.50E-02

Renewable Cost Declines

RenewableCostDeclineRate

Medium*

Use Spot Fuel Prices in Engineer Power Model

UseSpotFuelPricesInEngineerModel

No*

Use Additional Coal Intangible Cost

AdditionalCoalIntangibleCost

Yes*

Manual Coal Intangible Cost (short term)

ManualCoalIntangibleCostST

0

Manual Coal Intangible Cost (long term)

ManualCoalIntangibleCost LT

0

Maximum Coal Capacity Factor

MaximumCoalCF

0.9

Maximum Gas Capacity Factor

MaximumGasCF

0.9

Proportion of (2020-21) Covid adjustment passed on to engineer model power demand

EngineerModelProportionOfCovidFactor

0

Override Capacity Factor if below (Wind and Solar)

CFOverrideIfBelowWndSol

0.1

Override Capacity Factor if below (Others)

CFOverrideIfBelowFosOth

0.01

Override Capacity Factor if below (All)

CFOverrideIfAbove

1

Proportion of coal capacity that can be retired

MaxCostBasedEarlyRetirement

0.8

Minimum Thermal Efficiency

MinimumThermalEfficiency

0.1

Coal and Gas Power Purchase Agreements

Proportion of PPAs in Coal and Gas Generation

PPAProportionCoalGas

0

Phase out any coal and gas PPAs?

PhaseOutCoalAndGasPPAs

Yes*

Phase begins when?

YearPPACoalGas

2023

Phase out coal and gas PPAs over n years?

YearsToPhaseOutPPAs

5

Short Term Storage Parameters

Percent allocation of ST storage costs to VRE

AllocateSTStorageToVRE

1

Total hours short term storage for 100% VRE

TotalHoursStorageFor100pcVRE

9

kwh storage to kw interface ratio (hours)

StorageToInterfaceRatioSTStorage

2

Long Term Storage Parameters

Percent allocation of LT storage costs to VRE

AllocateLTStorageToVRE

0.33

Starting point of long term storage requirement (%VRE)

StartingPointWhenLTStorageIsNeeded

0.75

GW electrolyzer per Gwy/y for 100% VRE (%)

LongTermStorageFor100pcVRE

1

Storage hours for LT storage

StorageHoursForLTStorage

1000

Adjust Baseline Cost of Capital

Coal - adjust baseline cost of capital?

CostCapCoa

No*

Natural gas - adjust baseline cost of capital?

CostCapNga

No*

Oil - adjust baseline cost of capital?

CostCapOil

No*

Nuclear - adjust baseline cost of capital?

CostCapNuc

No*

Wind - adjust baseline cost of capital?

CostCapWind

No*

Solar - adjust baseline cost of capital?

CostCapSol

No*

Hydro - adjust baseline cost of capital?

CostCapHydro

No*

Other renewables - adjust baseline cost of capital?

CostCapOren

No*

Biomass - adjust baseline cost of capital?

CostCapBio

No*

Override Baseline Cost of Capital if selected

Coal - baseline cost of capital

CostCapBloverCoa

7.00E-02

Natural gas - baseline cost of capital

CostCapBloverNga

7.00E-02

Oil - baseline cost of capital

CostCapBloverOil

7.00E-02

Nuclear - baseline cost of capital

CostCapBloverNuc

7.00E-02

Wind - baseline cost of capital

CostCapBloverWind

7.00E-02

Solar - baseline cost of capital

CostCapBloverSol

7.00E-02

Hydro - baseline cost of capital

CostCapBloverHydro

7.00E-02

Other renewables - baseline cost of capital

CostCapBloverOren

7.00E-02

Biomass - baseline cost of capital

CostCapBloverBio

7.00E-02

Additional Cost of Capital Increment Policy Scenario

Coal - add cost of capital increment in policy?

CostCapAddCoa

No*

Natural gas - add cost of capital increment in policy?

CostCapAddNga

No*

Oil - add cost of capital increment in policy?

CostCapAddOil

No*

Nuclear - add cost of capital increment in policy?

CostCapAddNuc

No*

Wind - add cost of capital increment in policy?

CostCapAddWind

No*

Solar - add cost of capital increment in policy?

CostCapAddSol

No*

Hydro - add cost of capital increment in policy?

CostCapAddHydro

No*

Other renewables - add cost of capital increment in policy?

CostCapAddOren

No*

Biomass - add cost of capital increment in policy?

CostCapAddBio

No*

Policy Scenario Cost of Capital Delta if selected

Coal - Cost of Capital Delta

CostCapDeltaCoa

0

Natural gas - Cost of Capital Delta

CostCapDeltaNga

0

Oil - Cost of Capital Delta

CostCapDeltaOil

0

Nuclear - Cost of Capital Delta

CostCapDeltaNuc

0

Wind - Cost of Capital Delta

CostCapDeltaWind

0

Solar - Cost of Capital Delta

CostCapDeltaSol

0

Hydro - Cost of Capital Delta

CostCapDeltaHydro

0

Other renewables - Cost of Capital Delta

CostCapDeltaOren

0

Biomass - Cost of Capital Delta

CostCapDeltaBio

0

Policy Scenario Cost of Capital Override if selected

Coal - Cost of Capital Override

CostCapOverCoa

0

Natural gas - Cost of Capital Override

CostCapOverNga

0

Oil - Cost of Capital Override

CostCapOverOil

0

Nuclear - Cost of Capital Override

CostCapOverNuc

0

Wind - Cost of Capital Override

CostCapOverWind

0

Solar - Cost of Capital Override

CostCapOverSol

0

Hydro - Cost of Capital Override

CostCapOverHydro

0

Other renewables - Cost of Capital Override

CostCapOverOren

0

Biomass - Cost of Capital Override

CostCapOverBio

0

Allowed New Investments Override if selected

Coal - New Investment Override

NewInvCoa

If Present*

Natural gas - New Investment Override

NewInvNga

If Present*

Oil - New Investment Override

NewInvOil

If Present*

Nuclear - New Investment Override

NewInvNuc

If Present*

Wind - New Investment Override

NewInvWnd

Yes

Solar - New Investment Override

NewInvSol

Yes

Hydro - New Investment Override

NewInvHyd

If Present*

Other renewables - New Investment Override

NewInvOre

If Present*

Biomass - New Investment Override

NewInvBio

If Present*

Allowed New Investments (Date of Coming Online)

Coal

NewInvCoaYear

2019

Natural gas

NewInvNgaYear

2019

Oil

NewInvOilYear

2019

Nuclear

NewInvNucYear

2030

Wind

NewInvWndYear

2019

Solar

NewInvSolYear

2019

Hydro

NewInvHydYear

2030

Other renewables

NewInvOreYear

2030

Biomass

NewInvBioYear

2019

2 Summary of the approach and applications

2.1 Background and introduction

Ending poverty while managing climate change are defining challenges of this century. In recent years, these twin objectives have become enmeshed normatively and enshrined institutionally. In the last three years, 193 countries committed to achieving 17 Sustainable Development Goals (SDGs)—from tackling poverty, hunger, and gender disparities to improving health, energy access, and education. In addition, 195 countries committed in the Paris Agreement to limit global warming to “well below” 2 degrees Celsius by the end of this century. Notably, over 130 developing countries committed to national emissions abatement (through Nationally Determined Contributions, NDCs), for the first time. As a result, these countries need policy instruments to help them achieve their SDGs and NDCs.

Environmental tax reform (ETR) has been proposed as one of the important parts of our toolbox to do so. ETR can help developing countries reap substantial benefits, far beyond those of climate action.

More than two decades of research in development and environmental economics suggests that the welfare of ETR effects are likely to be more positive in developing countries than is commonly understood. Development co-benefits, such as direct improvements in human health or reductions in congestion and accidents, can be very large in developing countries, where air pollution kills millions and congestion reduces the benefits from agglomeration externalities and urbanization. ETR can also help finance ministries raise much-needed domestic funds at lower cost than some conventional sources of public revenues. These revenue gains can help expanding public expenditure, building health care and social protection systems, as well as investing to achieve universal access to infrastructure services such as modern energy, water and sanitation, mobility and access to information and communication. Because ETR can be simple to design and implement, low administrative capacity and political support need not hinder reform efforts.

In short, ETR can be the fiscal foundation upon which developing countries achieve both the SDGs and their NDCs. With the COVID-19 crisis, it is widely accepted that economic stimulus and restoring sound public finances are both needed, and that the recovery process can be designed to contribute to sustainable development. In particular, countries with financing constraints may want to consider energy subsidy reforms or even explicit carbon pricing to finance urgent needs in health, social sectors or growth-enhancing tax shifts. In the second phase of the recovery, when fiscal consolidation will become pressing, further discussion on

the potential of energy taxes is essential. In this context, finance ministries can use CPAT to evaluate such reforms. Another key function of the tool is to help mainstream carbon pricing into WB/IMF country work. CPAT is thus aimed at economists in the World Bank and the IMF as well as finance ministries (via the *Coalition of Finance Ministers for Climate Action*) and planning & line ministries.

The Climate Policy Assessment Tool (CPAT) is a spreadsheet-based tool to support these efforts. It allows for rapid estimation of effects of carbon pricing and fossil fuel subsidy reforms along several economic and non-economic dimensions. These include key macroeconomic variables, energy consumption, local and global pollutants, ‘development co-benefits’, distribution/equity and poverty. Its objectives are to:

- Help decision-makers and analysts do quick diagnostics on the potential benefits from explicit carbon pricing and fossil fuel subsidy reforms to inform SCDs and other country strategies;
- Provide first estimates of benefits across different dimensions (from tax revenues to health) to start an engagement with country counterpart and identify areas where more in-depth analyses are needed or promising.

For instance, CPAT is used for the EFI EU Regular Economic Report, which informs the EU’s consideration of environmental fiscal reforms; Mexico’s Public Finance Review, which examines its carbon tax; reviews of health-related tax reform option for Brazil and China (with Health GP); Ivory Coast’s PMR program; CGE and macrostructural models for Pakistan, Italy, Vietnam (within the MTI macro-modelling team); and for TA to Northern Macedonia’s on environmental tax reform review (ETR). CPAT can contribute to various reports products within the WB (SCDs, CPFs, DPOs, CEMs, State & Trends). CPAT has e.g. formed the analytical basis for a Bank-Fund [report](#) to the Coalition of Finance Ministers for Climate Action on carbon pricing.

CPAT is being developed jointly by the World Bank and IMF. It evolved from an earlier IMF tool, described in Appendix III of a 2019 Board Paper “[Fiscal Policies for Paris Climate Strategies](#)” and further applied in the IMF’s [October 2019 Fiscal Monitor](#) on “How to Mitigate Climate Change”. Background research for the various channels modeled has been completed by the CPAT team, notably through the studies “[Benefits beyond Climate](#)” and “[Getting Energy Prices Right](#)”.

2.2 CPAT dashboard and outputs

The CPAT tool is primarily a dashboard. It allows the user to input choices regarding the policy under investigation (such as a carbon tax trajectory, with different options for exemptions and recycling of the revenues) and modeling choices (e.g., choice between different data sources).

The tool produces a series of assessment and visualization of the impact of the policy scenarios on several dimensions including:

- mitigation and energy efficiency (i.e., the reduction in GHG emissions, changes in energy consumption);
- macroeconomic and fiscal aggregates (GDP, tax revenues);
- air pollution and health (concentration, but also mortality and morbidity);
- transport (road fatalities and congestion);
- distributional impacts (per consumption decile, but also by (urban/rural) sub-sample, and industrial cost changes)

A schematic view of the tool is provided in Figure 2.1, and a screenshot of the dashboard is provided in Figure 2.2. It is expected that the tool is used to explore various policy options, either in an interactive way, or to create country-specific document.

The tool is calibrated on 150 countries, but the user is advised to remain cognizant of data issues, which can affect the quality of the assessment. The Distribution module is more limited, as it depends on the specific treatment of household surveys. This module is currently available for 64 countries, but additional countries will be continuously added over time.

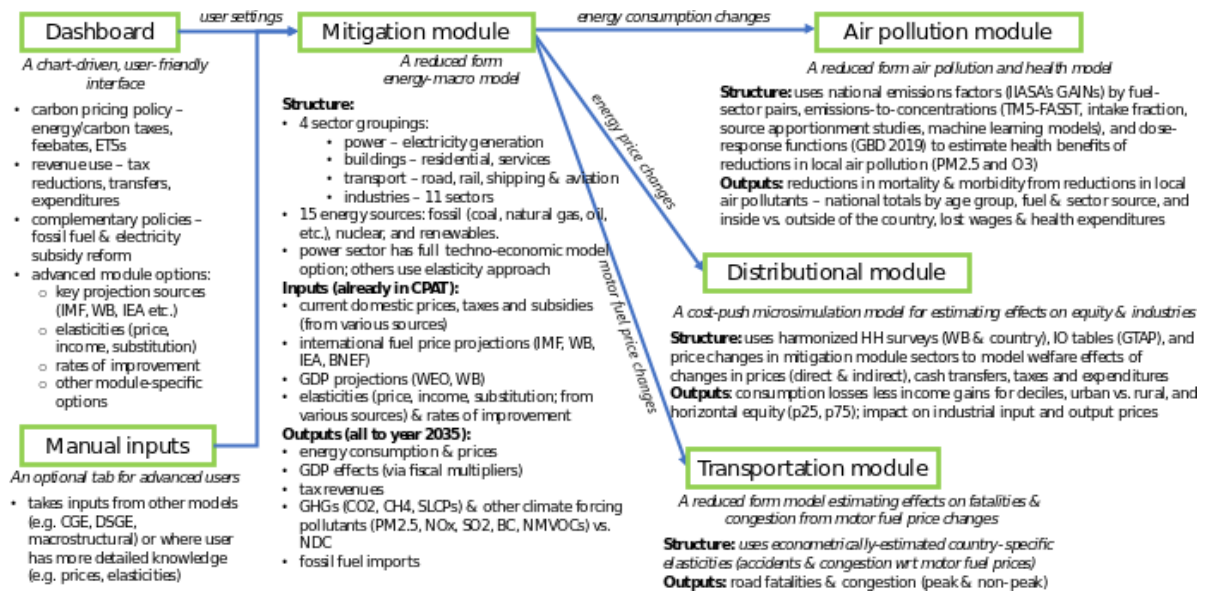


Figure 2.1: Summary of the CPAT v1.0 structure

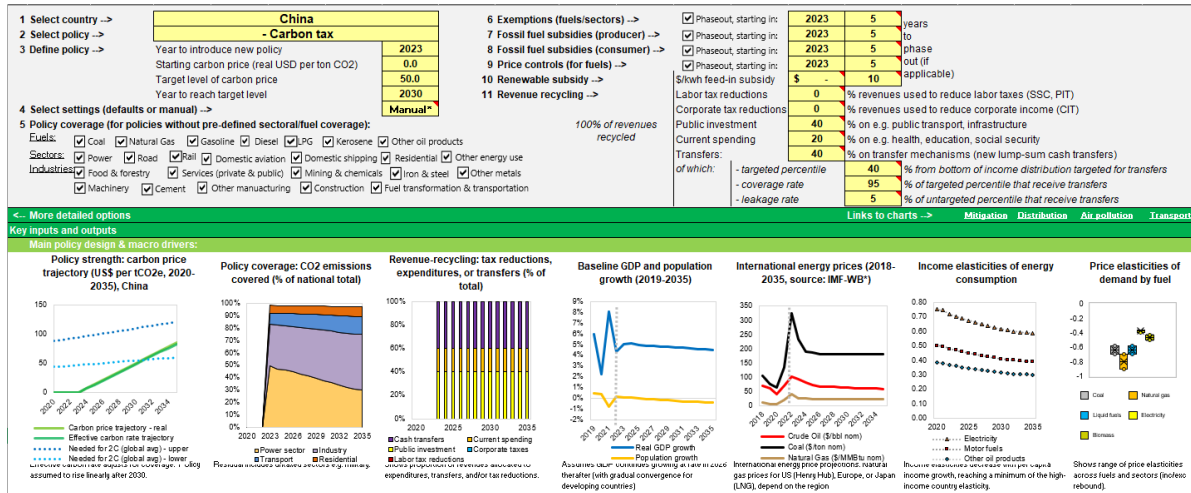


Figure 2.2: Illustration of the CPAT1.0 Dashboard (partial view, see the excel file for the full dashboard)

2.3 CPAT structure and methodology

This section provides a summary of the methodology (or methodologies) used by each of the modules, as well as basic comparison with state-of-the-art models. The value of CPAT is to be consistent with these state-of-the-art models in each dimension, and to provide *in one place all these dimensions together to facilitate analysis and comparisons and help teams prepare country diagnostics*. For the interested reader, in-depth methodological notes are available for each module ([CPAT chapters documentation here](#)).

2.3.1 Mitigation module

The mitigation module is a simplified reduced-form model of fuel consumption, deriving quantities under a baseline and a policy scenario broadly in line with more complex models (the IEA's World Energy Model, Enerdata POLES). The mitigation module's primary goal is to predict energy use, energy prices, emissions, carbon tax revenues, and GDP effects over the time horizon of CPAT (2019-2035). More details are available below in the methodological notes.

The module takes four types of inputs: (1) energy balances and price inputs; (2) external forecasts (baseline international energy prices and macro indicators); (3) parameter inputs (elasticities, fiscal multipliers); (4) user-specified policy inputs (for example, the level and coverage of a carbon tax, exemptions phase-out and other inputs).

The module's outputs include energy consumption by fuel type and sector, greenhouse gas emissions (CO₂ and other GHG such as leaked methane), fiscal revenues and GDP effects, price changes, power generation, and power sector investment.

The mitigation module forms the core of CPAT: when the user chooses a policy in the dashboard, the mitigation module works out the direct impact of the policy, displays it in the dashboard, and passes the outputs on to other modules (see Figure 2.1).

The general approach to determining baseline fuel consumption and the response to a carbon tax or other policy is a simplified, reduced-form model based on income and price elasticities. The changes in energy consumption from the base year are driven by energy prices (including the influence of mitigation policy) and real (total) GDP. Real GDP adjusts to changes in fiscal policy through multiplier effects. It can be considered the main driver of the baseline, while energy prices are the primary driver of any policy, such as a carbon tax. Exogenous changes to efficiency and the price of renewable energy are also drivers of fuel use and consumption.

For data and parameter sources, see the mitigation chapter. For example, elasticities with regard to prices and income are derived from Burke and Csereklyei (2016) using the relationship from Gertler et al. (2016)

The mitigation module includes two power sector models, an 'elasticity-based' model and a hybrid techno-economic dynamic model ('engineer model') of the power sector with explicit capital stock. The two models use the same power demand elasticities and separately consider power generation's costs by type. The user can either select 'average' – meaning an average of both models – or tailor the model using the engineer model alone

The 'elasticity-based' model uses marginal increases in fuel prices and price elasticities to determine the shares of each generation type. It is simple, transparently parameterized, easily explainable, and easily deployable in an Excel spreadsheet model used in previous versions of CPAT and IMF tools.

The techno-economic 'engineer' model explicitly models the capacity of different generation types, with capacity¹ expanding to meet desired power demand. Flexible capacity (gas and coal) is allocated according to marginal price, with a sigmoidal function of relative price. Investment is also a function of levelized cost, with a system penalty for the cost of integrating high levels of renewable penetration. Transmission losses are modeled as a fixed quantity of total generation.

The main advantage of the engineer model' is that it allows modeling decisions changing the stock of assets in the power sector (investment and retirement) and decisions changing the use of assets for power generation (dispatch). In addition, the model allows the user to define a Variable Renewable Energy (VRE) scale up rate. The rates reflect a 'linear' type constraint. It constrains generation in VRE additions to be a certain percentage of total generation (in gross additions, not net of retirements). The model is consistent with countries' generation

¹Capacity factors are assumed to be as in the base year (unless > those capacity factors are outside of normal ranges, when default > values are used)

capacities and makes it possible to investigate the radically different power systems consistent with high carbon prices, while the empirical ‘elasticity-based’ model is valid only for more marginal changes.

Finally, as one of the main outputs, the mitigation module estimates carbon pricing effects on GDP. CPAT adjusts the baseline GDP growth forecasts endogenously depending on different carbon pricing and revenue recycling scenarios. The module captures two channels: the fiscal effects and the impact on consumption. In the first channel, a carbon tax has both direct and indirect effects on GDP. The latter arises when the carbon tax revenues are recycled as a reduction of other taxes and/or increased government spending. We quantify these effects using the CPAT fiscal multipliers estimates. In the second channel, the change in GDP affects energy consumption and, therefore, the effective carbon tax revenues. This channel is captured by the income elasticities of energy demand.

CPAT uses four sources of fiscal multipliers: “Income-group” multipliers and “global” averages are obtained from the World Bank’s Macro-Fiscal Model (MFMod). “Estimated” multipliers are obtained econometrically from panels of high- and low-income countries created along the dimensions of income levels, regions, debt levels and trade openness. Country-specific multipliers are then obtained as weighted averages over the respective multipliers from each sample/subsample which the country is part of. Finally, since multipliers tend to be higher during expansions and lower during contractions, all baseline multipliers can be adjusted upwards and downwards by adding/subtracting one empirical standard deviation. This takes into account the uncertainty around empirical estimates and gives the CPAT user additional flexibility in choosing the appropriate set of multipliers. Finally, the user has the option to “manually” enter the preferred multipliers, thereby allowing for a thorough exploration of the uncertainty in these parameters.

A full summary for reviewers including a list of change and full information about the validation of the mitigation module against ex post studies and other models, is available in the mitigation chapter of this report. See section 3.9.

2.3.2 Air Pollution module

Policies aimed to reduce GHG emissions, such as carbon pricing, can lead to a reduction in ambient air pollution due to the co-emission of GHGs and local pollutants when burning fossil fuels. Local pollutants, such as BC, OC, NH₃, SO₂ and NMVOC are responsible for the formation of fine particulate matter (PM_{2.5}) and ozone (O₃) pollution. These pollutants contributed to 6.67 million deaths and 213 million DALYs in 2019 ([Institute for Health Metrics and Evaluation](#)). Air quality improvements will reduce mortality and morbidity and CPAT quantifies those effects as a co-benefits of carbon pricing.

The air pollution module is mostly based on models developed by external institutions and researchers, but also includes modeling developed specifically for CPAT. The main inputs are: (1) energy consumption in time and scenario by fuel type and sector from the Mitigation

module; (2) emissions factors net of projected average use of pollution control equipment, fuel processing and combustion method from GAINS model^[02_summary-4]; (3) concentrations of PM2.5 and ozone for the baseline year (2019); (4) emissions-to-concentrations relationships for ambient PM2.5 and ozone, based on source receptor matrices (TM5-FASST), regression analysis, source apportionment studies, intake fractions and machine learning models, (5) relative risk functions for exposure to PM2.5 and O3; and (7) population projections in time. Details are available in the [air pollution methodological note](#). Wagner et al. (2020)

The main results from the air pollution module are mortality and disability adjusted life-years (DALYs) attributed to air pollution (ambient and household) under the baseline and the carbon price scenario. Other outputs include the economic valuation of averted deaths (using a transferred value of the statistical life), health expenditure, working days lost due to pollution and market output losses due to morbidity and mortality.

Reduced-form approximations are used to estimate emissions, concentration of pollutants and health effects. We use and adapt the results of more complex models into simplified relationships. For instance, in the case of the relationship between emissions of pollutants and ambient concentrations of PM2.5 and ozone, CPAT includes the option to use the results from a linear emulator of a complex global chemical transport model. The results of the air pollution module are in line with other more complex models (see Figure 2.4a and Figure 2.4b), although both CPAT and the models to which we compare to are subject to uncertainty and the results may be sensitive to the assumptions used. We address this issue in CPAT by allowing the user to input local information, if available, and to switch among methodological options (with the best options possibly dependent on the country chosen).

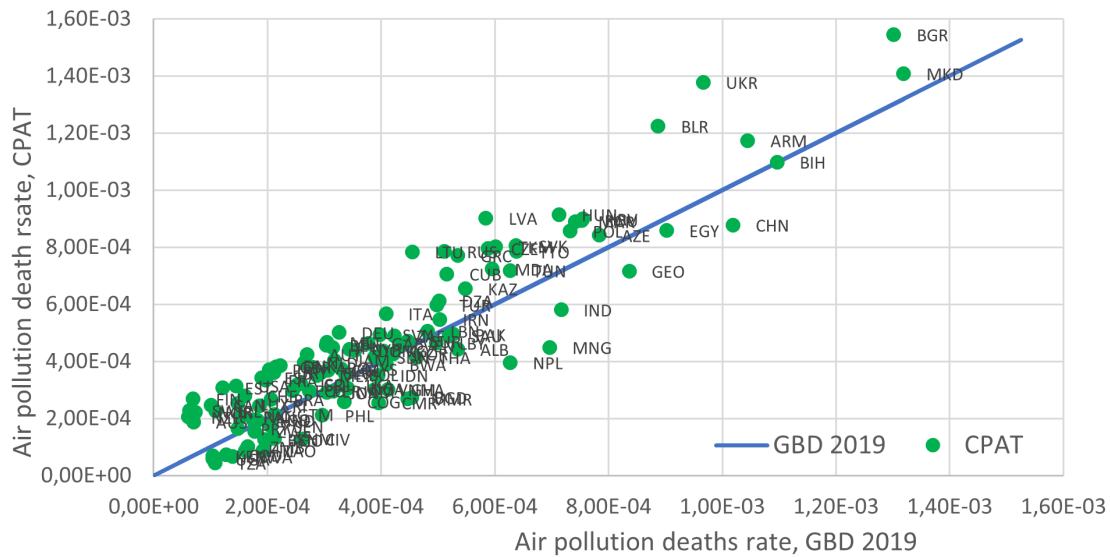


Figure 2.3: CPAT estimation of ambient air pollution death rates versus GBD2019 estimates

Source: CPAT results and GBD 2019 Risk Factors Collaborators. Note: Green dots represent CPAT results, and the blue line represents results from the external model. When the green dots are above the blue line (45 degrees line), CPAT estimates are higher, and when the green dots are below the line, CPAT estimates are lower.

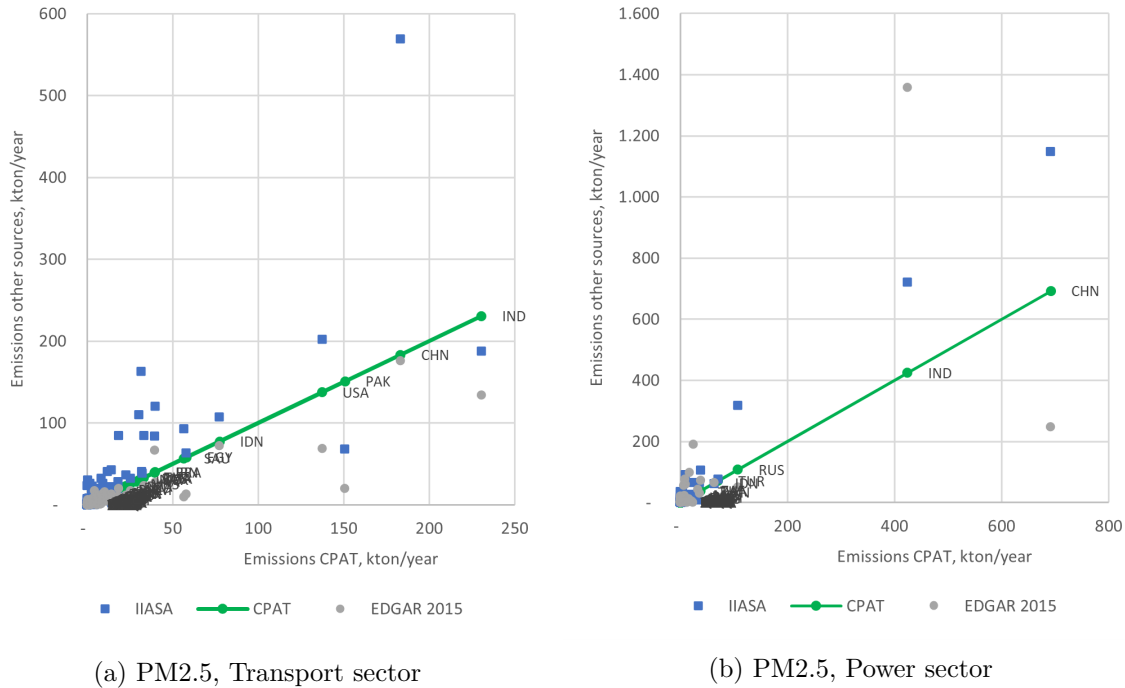


Figure 2.4: Comparison of PM2.5 emissions, CPAT and IIASA in 2020, EDGAR in 2015

Source: CPAT results, *Emission Database for Global Atmospheric Research (EDGAR)* and IIASA²

2.3.3 Distribution module

Income inequality, poverty and, more generally, social justice considerations are increasingly becoming a centerpiece of governments' fiscal policy decisions. With the COVID-19 pandemic leading to sharp increases in inequality and poverty, distributional concerns have become more relevant to decision-makers. In the realm of environmental fiscal reforms, equity and poverty considerations receive even more political attention than in the context of 'traditional' fiscal reforms. Public acceptability is strongly driven by the reforms' perceived fairness and impact on low-income households.

²IIASA. 2015. "ECLIPSE V5a Global Emission Fields - Global Emissions." 2015. <https://iiasa.ac.at/web/home/research/researchPrograms/air/ECLIPSEv5a.html>.

The Distribution Module of CPAT 1.0 aims to inform the spread of the immediate fiscal incidence *across* (vertical distribution) and *within* (horizontal distribution; see Figure 2.7) income groups, focusing on consumption effects and compensatory schemes. Tax-induced consumer price changes and revenue recycling in the form of direct transfers have been at the center of the literature on fiscal redistribution, since such salient, short-term effects are arguably the most relevant from a political economy perspective.³ More details are available in the [Distribution methodological note](#) (with [detailed country coverage](#)).

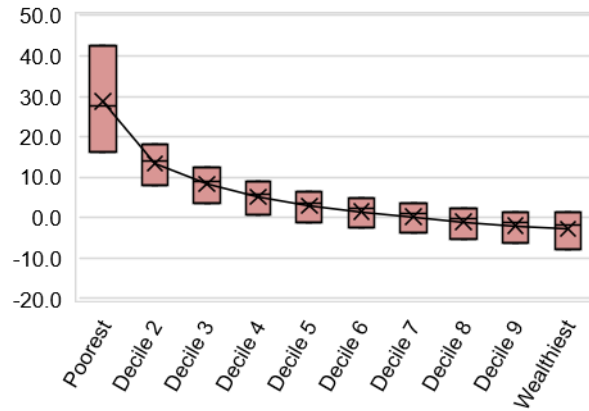


Figure 2.5: Net distributional effect with cash transfer: Horizontal distribution of relative consumption effects (% consumption for \$50 Carbon tax per tCO₂e in 2022), China

The Distribution Module allows the user to estimate the carbon tax incidence on consumption, taking into account the direct effect from the use of fuels, as well as the indirect effect from the consumption of other, non-fuel/-energy goods and services. We follow the standard approach in the literature, combining household budget survey (HBS) information with input-output (IO) data, adjusted such that they yield the same effective carbon price revenues as the ones produced by the Mitigation Module. Country-fuel-sector- price increases are based on scenario-specific estimates from CPAT’s Mitigation Module. Further, the user is provided with two options to relax the typical IO assumptions of full cost-push impacts and absence of behavioral adjustments. Additionally, there is one option to rebate the price increases of a country’s primary cooking fossil fuel to selected bottom deciles to help prevent them from switching to biomass.

Four modes of direct and indirect transfer schemes can be simulated, once the user inputs the share of revenues allocated under each scheme type: i) new or existing targeted transfers (for which the user can decide the targeted percentiles, among other features); ii) transfers

³Note that longer-term structural effects on wages and overall employment tend to positively outweigh consumption-side effects, as they tend to be positive, larger and more often progressive (Metcalf 2019; Markandya et al. 2017). Source-side effects and their distribution, beyond compensation measures, will be priorities in the development of CPAT v2.0.

towards public investment in infrastructure access; and iii) scaling up an existing social protection scheme (following the targeting of the initial scheme), and iv) reforming countries' personal income tax (PIT) schemes. The revenue amounts available for redistribution are based on scenario-specific estimates from the Mitigation Module. New or existing targeted transfers are universal among the targeted percentiles, while infrastructure transfers are targeted to those households without initial access to clean water, affordable electricity, clean sanitation, Information and Communication Technologies (ICT), or public transport, based on HBS microdata. Revenue recycling that increases current public spending is proportional to the existing social protection schemes, such as social assistance, insurance, or in-kind benefit schemes. Further to the above, transfer scheme targeting is also available for decile-specific population shares that are below international poverty lines (incomes of 1.9 or 3.2 2011 PPP USD/day) via "poverty-conditional cash transfers".

Both negative consumption effects as well as positive compensation scheme effects are expressed as shares of pre-reform consumption and in absolute, per-capita monetary terms on a decile level, separately for the rural, urban and overall (or national) populations.⁴ For vertical distribution graphs, the user can further choose between decile mean and median consumption data inputs. Horizontal distribution between the 25th and 75th percentile of consumption data inputs within each decile is available for consumption effects (both absent as well as net of compensation schemes).

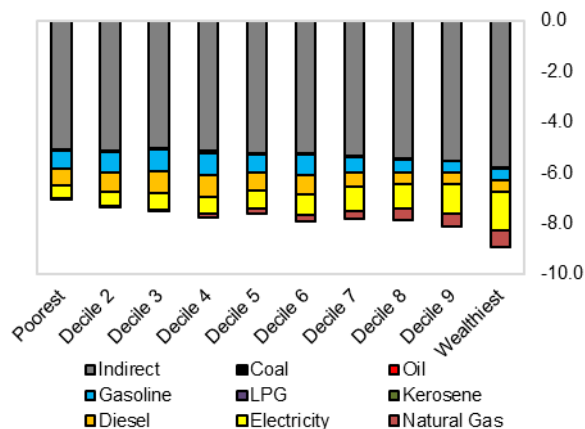


Figure 2.6: Relative mean consumption effect (% consumption for \$35 Carbon tax per tCO₂e in 2022), Cote d'Ivoire

⁴Note that un-adjusted consumption effects should be interpreted as upper-bound estimates in terms of Laspeyres Variation, while positive compensation effects should be interpreted as lower-bound estimates, capturing only the direct monetary benefit, but not the economic co-benefits of, for example, improved health, education, and opportunity.

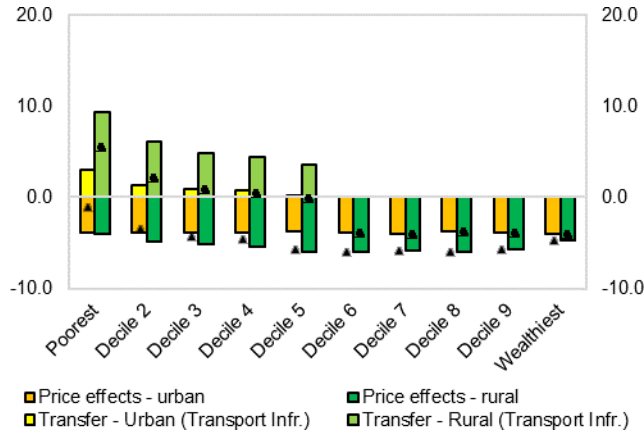


Figure 2.7: Relative mean consumption effect, urban vs. rural (% consumption for \$35 Carbon tax per tCo2e in 2022), Cote d'Ivoire

2.3.4 Road Transport module

Carbon pricing impacts fuel prices and shapes driving behavior and can thereby contribute to internalizing externalities from driving. Increases in fuel prices predictably lead to reductions in vehicle-miles traveled (VMT). This may be a result of people transitioning to other transport modes, e.g. public/collective transport options, choice of residence and workplace location or behavioral changes including car-pooling, trip frequencies and driving behavior (aggressive vs. fuel-efficient acceleration). As road traffic has many externalities aside carbon emissions, the reduction in VMT also leads to a reduction in transport-related externalities such as congestion, accidents and road damage. To estimate the magnitude of these co-benefits, the road transport module quantifies the effect of a user-defined carbon price or road fuel tax on (1) the intensity of congestion as measured by the time lost relative to free-flowing traffic, (2) the number of road fatalities, and (3) the maintenance cost due to road damage.

The Road Transport module is based on elasticities that we estimate using an international country-year level dataset. This dataset is compiled from many sources and describes road transport, as well as general demographics and economic variables. The dataset covers the time from 1994 to 2019 and 180 countries, so that we can use within-country and between-country variation for identification. We estimate elasticities with respect to fuel prices and with respect to fuel taxes, as well as short and long-run elasticities. Our country-specific elasticities are based on global coefficients and country-specific covariates.

The magnitude of the resulting elasticities are broadly in line with the literature: for a 10% fuel price increase from a carbon tax, total vehicle-km traveled decrease in the short run on average by 3.5%; congestion levels decrease by 4.5%; accident fatalities decrease by 2.9%; and road damage by decreases by 2.0% in the long run.

The estimated elasticities are used within CPAT to produce policy forecasts of total vehicle-km

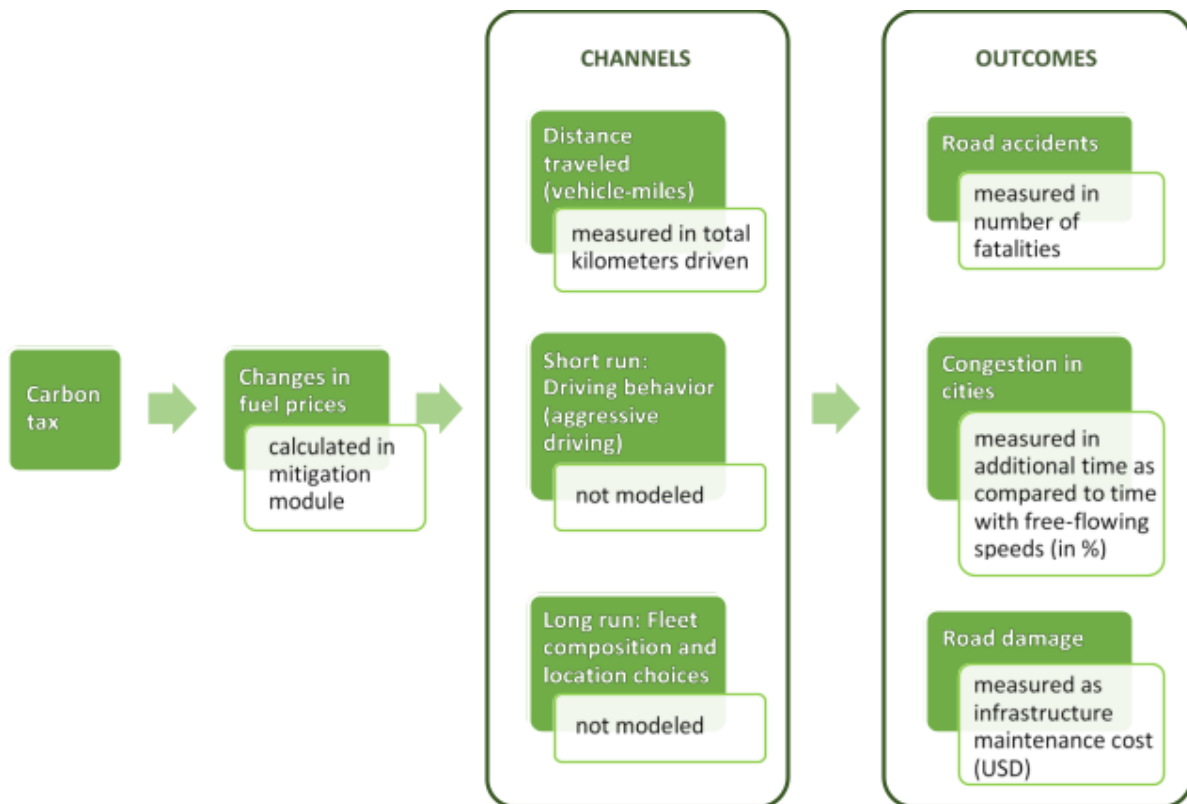


Figure 2.8: Input and output of CPAT's Road Transport module

traveled, congestion levels, accident fatalities and road damage cost. By choosing a country and using different parameters for a policy in the dashboard, the user obtains a series of graphs showing the time series with and without the policy, as well as the policy impact given by the difference of the two time series.

3 Mitigation module

The Mitigation Module¹

World Bank	IMF
Paolo Agnolucci	Simon Black
Daniel Bastidas	Victor Mylonas ²
Alexandra Campmas ³	Ian Parry
Faustyna Gawryluk	Nate Vernon
Olivier Lelouch	Karlygash Zhunussova
Stephen Stretton ⁴	

3.1 Executive Summary and Reviewer Guide

3.1.1 Introduction

The mitigation module lies at the heart of CPAT. It is based on a simplified reduced-form model of fuel consumption, with two alternative power sector models, one of which is a simplified structural technoeconomic power model.

¹The mitigation chapter of the CPAT documentation was prepared by Alexandra Campmas, Daniel Bastidas, Olivier Lelouch, Faustyna Gawryluk, Paolo Agnolucci, and Stephen Stretton. Some sections are based on earlier papers by Ian Parry, Simon Black, Karlygash Zhunussova, Nate Vernon, Alexandra Campmas, and Stephen Stretton. Thanks to the whole CPAT team – and, in particular, to Simon Black, Karlygash Zhunussova, Paulina Schulz Antipa, and Samuel Okullo for useful comments, clarifications, and assistance in preparing this paper. CPAT has benefited from the extremely helpful comments of our initial reviewers in early 2021 including, among others, Charl Jooste and Claire Nicolas; thanks also to Claire and Adam Suski for providing EPM comparison data. CPAT relies on the assistance of many parties for data and support, including other WB Global Practices (including Phillip Hannam from Energy GP, who helped develop the techno-economic power model) and other academic groups, including IIASA (who provided emissions factors). Thanks to Dirk Heine, Stephane Hallegatte, Simon Black, and Ian Parry for leadership and direction, and for originating what became CPAT. Thanks also to Somik Lall for leadership and guidance.

²Victor Mylonas (WB) is listed on the IMF side reflecting his historical contribution to the mitigation module when working at the IMF.

³Corresponding author: Alexandra Campmas(acampmas@worldbank.org)

⁴Corresponding author: Stephen Stretton (stretton@worldbank.org)

The mitigation module's goal is to predict energy use, energy prices, emissions, carbon tax revenues, economic costs, and GDP effects for a baseline and a policy scenario (carbon pricing, fuel taxes, energy efficiency policies, renewables subsidies, feebates, etc.), over the time horizon of CPAT (2019-2035).

To this end, the module is built around different inputs, including (1) energy balances and price inputs; (2) external forecasts (baseline international energy prices and macro indicators); (3) parameter inputs (elasticities, fiscal multipliers, etc.); (4) user-specified policy inputs (for example, the level and coverage of a carbon tax, exemptions and exemption phase-outs, and other inputs).

These inputs inform the calculation steps in which: (1) sectoral energy prices, including the effect of pricing policy, are determined; (2) fuel use in the buildings, transport, and industry are estimated; and (3) electricity production costs are calculated to feed the two power models, which then determine generation, investment, etc.

The module's outputs include energy consumption by fuel type and sector, greenhouse gas emissions (CO₂ and other GHG such as methane), fiscal revenues and GDP effects, price changes, power generation, and power sector investment. The structure of the rest of this document is as follows:

- Overview
 - Introduction
 - Summary of Mitigation Module
 - Niche and Use Case
 - Critical Policy Modelling Choices
 - Data
 - Testing and Validation
 - Status of Upgrades since last time
 - Caveats
 - Notation
- Prices and taxes;
- Energy consumption (excluding power supply);
- Power supply prices and models;
- Emissions of CO₂ and other GHG;
- Fiscal Revenues;
- Monetized welfare estimates;
- Validation: including regression, comparison with other models, and hindcasting.
- Appendices including:
 1. Appendix A - Macro data of CPAT: Sources and codes;
 2. Appendix B - Energy balances;
 3. Appendix C - Prices and taxes methodology;
 4. Appendix D - Examples of NDC calculations;

5. Appendix E - Parameter options in the mitigation module;
6. Appendix F – Notation in CPAT; and
7. Appendix G – Data sources.

3.1.2 Summary of Methodology

The mitigation module is a simplified reduced-form model of fuel consumption, deriving quantities under a baseline and a policy scenario broadly in line with more complex models (the IEA’s World Energy Model, Enerdata POLES – see 3.8.3 Model comparisons). The mitigation module’s goal is to predict energy use, energy prices, emissions, carbon tax revenues, economic costs, domestic environmental co-benefits, and GDP effects over the time horizon of CPAT (2018-2035) for a wide range of mitigation instruments (carbon pricing, fuel taxes, energy efficiency policies, renewables subsidies, feebates, etc.). The main drivers of the emissions projections are GDP growth (including GDP-per-capita and population), income elasticities, and rates of technological change. Fuel use responses to policies are driven principally by proportional changes in fuel prices caused by projected market dynamics and government policies (including carbon prices).

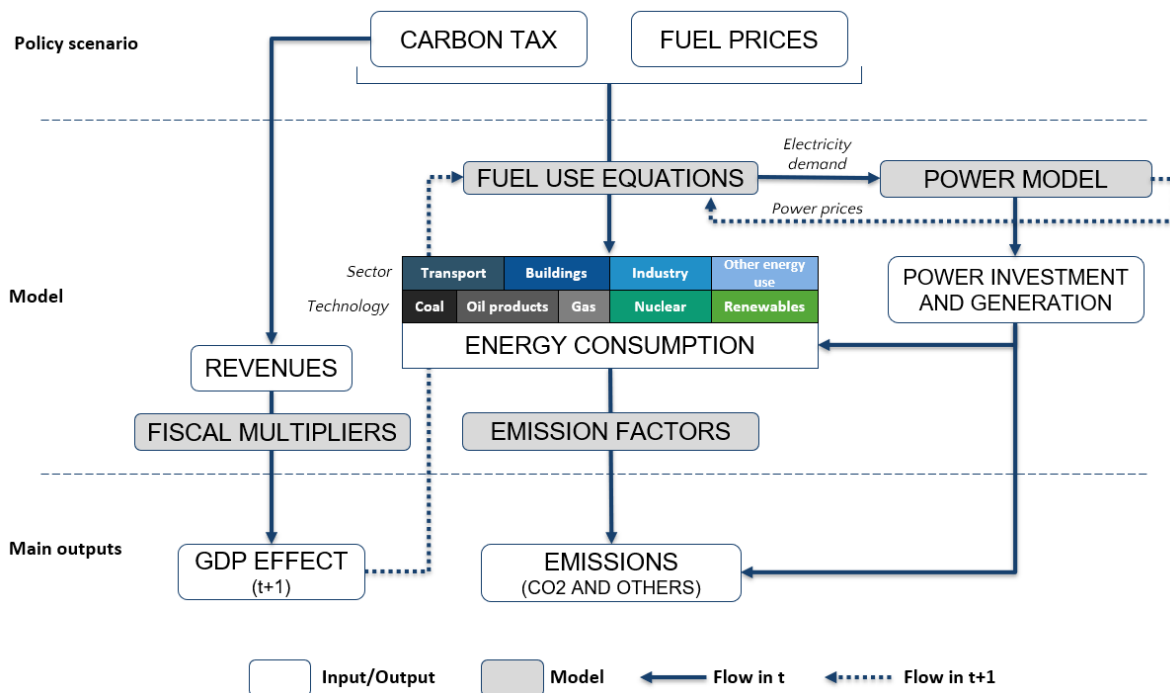


Figure 3.1: Overview of the mitigation module

The mitigation module relies on several inputs and provides numerous outputs. The module is at the core of CPAT, as its results feed into other modules.

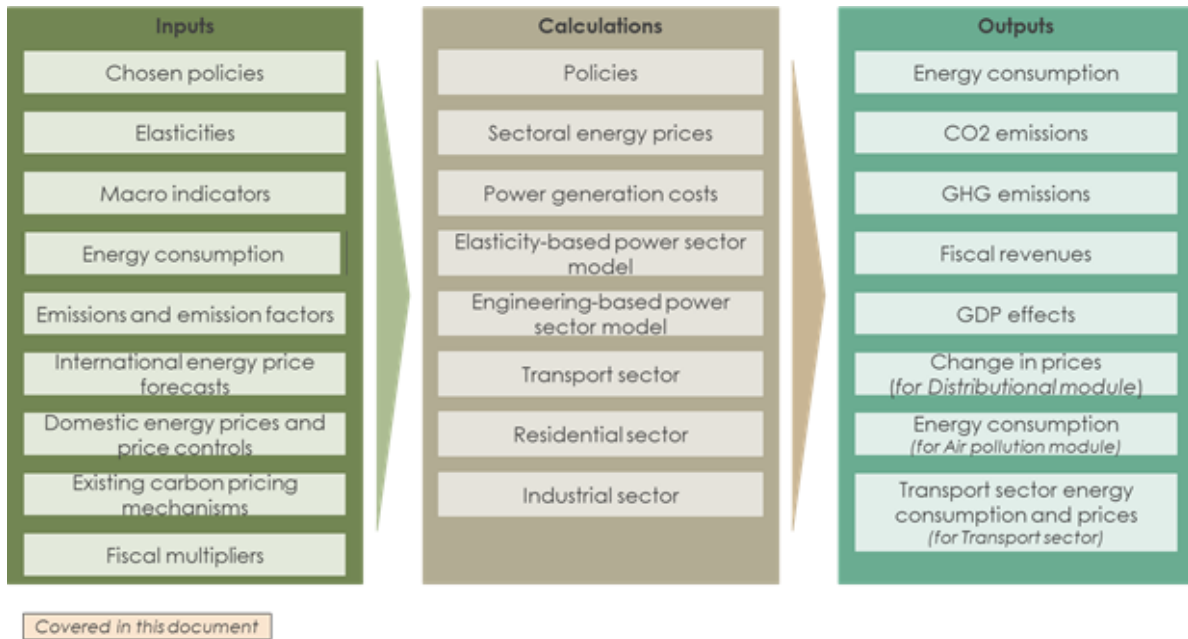


Figure 3.2: Overview of the mitigation module’s inputs and outputs

The general approach to determining baseline fuel consumption and the response to a carbon tax or other policy is a simplified, reduced-form model based on income and price elasticities.⁵ The changes in energy consumption from the base year are driven by energy prices (including the influence of mitigation policy) and real (total) GDP. Real GDP (which is the primary driver of the baseline) adjusts to changes in fiscal policy through multiplier effects (see the Chapter on Multipliers). Exogenous changes to efficiency and the price of renewable energy are also drivers of fuel use and composition.

The mitigation module comprises two power sector models and simple models for industry, transport, and buildings. The two power models, the ‘elasticity-based’ model and the hybrid techno-economic dynamic model (‘engineer model’) of the power sector with explicit capital stock use identical power demand elasticities and separately consider power generation’s costs by type. For ‘off-the-shelf’ usage of CPAT, we recommend an average of the two models. For more tailored work, we recommend using the engineer model.

The elasticity-based model requires only minor tailoring and checking. As a result, it makes no distinction between short-term and long-term behavior. It also fails to distinguish between dispatchable and non-dispatchable generation types. The engineer power model fills this gap by separating investments, retirement, and dispatch decisions. It includes countries’ generation capacities and makes it possible to investigate the radically different power systems compatible

⁵Income and price elasticities are based on a literature review. Income elasticities might depend (implicitly) on the level of GDP per capita (user option).

with high carbon prices. However, the model still cannot account for inflexibility, off-price policies, and local price variation (e.g., coal). Due to the constraints of Excel, it can only approximate the temporal match between electricity supply and demand.

The module's outputs include energy consumption by fuel type and sector (i.e., buildings, transport, and industry). They are estimated based on a fundamental model structure described in an IMF paper.^[^03_mitigation-6] Energy use responds to energy prices and real GDP. Additional outputs include greenhouse gas (GHG) emissions (i.e., CO₂ and other GHG emissions such as leakage methane which represents small amounts of GHG gases), fiscal revenues and GDP effects, economic efficiency costs, price changes, power generation, and power sector investment.

To ensure that the model is correctly fitted, specific calibrations are undertaken for the observed years, i.e., 2019, 2020, and 2021 (and beyond if necessary and if data are available). In particular, due to the unprecedented global economic shock induced by Covid-19 and Ukraine invasion, energy prices may have behaved in an “anomalous” way, leading the model results to deviate from the observed data. This calibration ensures a proper starting trajectory for the model.

The rest of this section is intended to help reviewers navigate the Mitigation documentation by highlighting the tool's key components, and the main conclusions resulting from the validation analysis of CPAT.

3.1.3 Niche & Use cases for CPAT

CPAT requires minimal training to be used effectively. Computer literacy, basic familiarity with Excel, and some understanding of economic and climate concepts. Flexibility is built-in for the more advanced user, to allow for different assumptions than those in the default assumption set and for choosing among various data inputs. Advanced users can also input their own data.

Although CPAT is powerful even on its own, it is still advisable to use it alongside other tools that may have a more granular representation, of say, technological detail, sectors, feedback mechanisms, trade linkages, behavioral responses, etc. CPAT is designed to be light on resource and skill needs, providing a rapid first-cut analysis when one seeks to test various carbon pricing designs.

The carbon tax is the most effective instrument for emissions reduction in CPAT. By default, its coverage spans the whole economy, but the user can also set this to select sectors. The ETS covers the whole economy by default with the option also to select coverage. A key assumption is that the ETS and carbon tax are equivalent in a frictionless market with full auctioning. While the ETS design lets the user select prices (rather than quantities), frictions imply that ETS is not as effective at reducing emissions as a carbon tax. The user can choose the initial

carbon tax level, when to commence carbon pricing, the target carbon price, the year that the target level is achieved, and the sectoral coverage of the carbon tax.

Strengths and weaknesses of CPAT in relation to carbon pricing schemes:

Country's needs	Yes/No	Remarks
Understanding which instrument (ETS or tax) to choose.	No	Like most other deterministic models, CPAT assumes that the ETS yields the same price as a carbon tax and does not currently consider offset markets.
Assessing the impacts of carbon price on the economy, employment, energy/fuel prices	Yes	CPAT provides an assessment of macroeconomic performance, energy consumption and price changes, emission reductions, distributional consequences, and co-benefits (health and traffic) of carbon pricing reform.
Different allowance allocation mechanisms	Partial	CPAT has an effectiveness and revenue parameter for ETSs.
With and without consideration of offsets	No	See above
Different carbon tax rates for different sectors	Yes	CPAT has a consistent carbon price that can be exempted by sector and/or fuel type. There is also an excise reform table that allows fuel and sector-specific pricing.
The potential distributional impacts of introducing a carbon price	Yes	This requires household expenditure survey data. If this data is not already available within CPAT, it must be entered to access the reform's distributional consequences.
Understanding the potential "co-benefits" of introducing a carbon price.	Yes	Reduction in local pollutants and traffic co-benefits associated with carbon pricing reform are currently represented in the model.
Are all sectors represented in CPAT?	Yes	CPAT brackets the economy into 17 sectors.
Does CPAT account for pre-existing policies?	Yes	CPAT also allows the user to phase pre-existing subsidies, for instance, or exemptions if these have been added during instrument design.

3.1.4 Critical Policy and Modelling Choices

The reviewer should be aware of a few critical modeling choices.

First, the user has the option to as well as a carbon price to phase out fossil fuel subsidies. Those are shown on the top right of the main policy panel.

specific value for some countries that adds an intangible cost to coal generation (representing regulations not captured in CPAT plus lack of flexibility relative to natural gas). That adjustment can be turned off in the power setting panel (around row 131). The setting is calibrated to current coal shares and long-term IEA projections.

3.1.5 Data choices in CPAT

3.1.5.1 Key data used

For more information, Appendix G, ‘Data sources,’ gives an overview of the data used in the mitigation module.

The main data sources are IEA data, various World Bank data sources, IIASA data for emissions, and Energy Prices and Energy projections are primarily from the IMF (from multiple processes).

3.1.5.2 Key parameters and choices

Sections of the Mitigation documentation detailing the key parameters and their methodology, if estimated:

- Elasticities: *3.3.5 Income and Price Elasticities of Demand*
 - Autonomous efficiency improvement: *3.3.5.6 Rates of technological change and exogenous rebound effects and 3.4.2.3 Power demand. Also, see caveats.*
 - Renewable scale up rate: *Section 3.4.2.4 ‘Power supply.’*
 - CapEx: *Section 3.4.4 ‘Power sector data sources and parameter choices.’*
-

The following key parameters in CPAT rely on different data sources or assumptions:

- Elasticities concerning prices and income are derived from Burke and Csereklyei (2016) using the relationship from Gertler et al. (2016)
- The exogenous time trend or autonomous efficiency improvement is set based on IEA’s data and experts’ judgment. Values are different across sectors and fuels. See the caveats section.

Scale-up limit (MW)	Wind	Solar
Observed CF	21.3%	16.4%
Limit (% tot gen)	2.0%	2.0%
Limit (MW)	17,412	22,536
Historical Avg (MW)	2,658	3,502
Historical Max (MW)	4,148	9,204
Generation (GWh)	69,949	50,563
Capacity	37,505	35,089
Limit (% tot gen)	32,474	32,474
Total Generation (GWh)	1,623,691	

- Renewable scale up rates are set so that the user can choose a low, medium, high, or very high rate, corresponding to 1, 2, 3, and 4% of additional generation (as a proportion of total generation) per year, respectively. In addition, the CPAT dashboard provides transparency on country-specific scale-up historical rate, should the user decide to use a more specified rate as the one defined under the settings.
- The engineer power model relies on forecast CapEx, subject to a learning rate methodology for renewable energies.

3.1.5.3 Key calibration exercises

Calibration exercises are presented under the corresponding section. In particular:

- Overall energy use through Covid adjustment in 2020 and 2021: *Section 3.3.4.4 'Calibration of overall energy use through Covid adjustment in 2020 and 2021.'*
 - Calibration in the engineer power model: *Section 3.4.2.4 see sub-section 'Calibration.'*
 - Emissions: *Section 3.5 'Emissions.'*
 - Long-term storage is based on electrolyzes *Section 3.4.2.5 see sub-section 'Long-term storage.'*
-

A calibration exercise is performed for some key variables to prevent the model from deviating from observed data (i.e., for 2019 to 2021) and ensure a proper starting trajectory, particularly in the context of Covid. Against this background, the following adjustments have been made:

- **Overall energy use through Covid adjustment in 2020 and 2021:** Due to the unprecedented global economic shock induced by Covid-19, the energy consumption factor makes an ad hoc adjustment to the model and is calibrated using emissions outturn as the overall numeraire in 2020 and 2021.

- Calibration in the engineer power model:
 - **Total electricity generation:** A COVID adjustment factor can be used to calibrate total electricity generation. The latter, estimated by the model, is compared to observed data (IEA, 2020). It is worth mentioning that the default in CPAT does not account for this calibration, but this calibration can be turned on.
 - **Share of coal:** The share of coal in electricity generation is calibrated to observed data in 2019 and 2020 (IEA, 2019 and 2020). The calibration uses an additional implicit price for coal – if necessary – to match the observed share of coal.
- **Emissions:** In 2019, both CO_2 and CH_4 energy-related emissions are scaled to UN-FCCC inventory emissions, meaning they are multiplied by a factor such that base-year emissions are equal in the model and the inventory.
- **Long-term storage is based on electrolyzers:** Given its interseasonal storage and geographic independence, we focus on the costs of electrolyzers for storage. This storage cost is thus assumed as long-term storage and is measured with the interface (i.e., electrolyzers) as the numeraire.

3.1.6 Testing and validation summary

The full validation analysis of the mitigation module is presented in Section 3.8 of the documentation.

The validation of the mitigation module is composed of several elements:

Analysis performed	Main conclusions
Elasticities estimations. As CPAT is mainly driven by elasticities with respect to prices and economic activity, an econometric analysis is carried out to compare the elasticities used in CPAT and those obtained from empirical analysis.	The empirical validation pointed out that the elasticities with respect to price and economic activity in CPAT tend to be in the same ballpark as those estimated here, with some exceptions related to road transport and the service sector.

Analysis performed	Main conclusions
Comparison of CPAT against other models. ⁶ This analysis comprises comparisons between CPAT and Enerdata, IEA, and EPM models.	Overall, the comparison analysis shows comparable results between CPAT and other models with a few exceptions most likely linked to different components in fuel aggregation, divergent assumptions regarding nuclear, country-specific divergence (e.g., Russia), or Covid adjustment.
Ex-post studies. This section presents the literature's estimates of the effectiveness of carbon pricing with respect to emissions and compares them to the CPAT results.	When looking into the range of CPAT's estimates across all sectors, results are comparable with those of the literature. At the sector level, the power sector records the highest decrease in the long run, which is consistent with the literature.
Hindcasting. The hindcasting exercise aims at testing CPAT's forecasts against observed data. It searches to evaluate the performance of the assumptions used when trying to reproduce historical information.	For the countries analyzed, CPAT generally fits the trend of observed data. There are some discrepancies and periods where gaps appear. However, for certain periods/countries, discrepancies of volatile magnitudes appear between CPAT projections and observed emissions. While this may result from implementing policies that were not modeled in the exercise, it can also result from discrepancies in price forecasting.
Parameter Sensitivity Analysis. The analysis explores the sensitivity of a set of selected parameters.	The sensitivity of the parameters to CPAT to CO2 emissions ranges from no effect to very sensitive when focusing on the relative changes (i.e., CO2 emissions reduction relative to the default parameter).

3.1.7 Status of upgrades since the last review

There have been many upgrades to CPAT since the last review, and the table below gives a partial list to give the reviewer an idea of the improvements. The version log in CPAT itself provides an exhaustive list.

Feature	Components	Status
Complete documentation	Full documentation, including but not limited to Biomass substitution; Power sector parameters; other mitigation features (e.g., NDCs)	Complete

⁶Please note that more comparisons are available upon request.

Feature	Components	Status
Validate CPAT historically	Basic global validation of income elasticities	Complete
Validate CPAT historically	Panel data estimate of income elasticities and time trends	Complete
Shareability	Transform all non-shareable (proprietary) data into a shareable form	Complete
Single Time Period for Simplicity	CPAT, for a while, had short- and long-term components to the price elasticity. We eliminated these for now as the goal is not a short-term prediction but medium-term accuracy and simplicity	Complete
Update of power data	Full update and sourcing of power sector data (CapEx, variable and fixed OpEx, Efficiency, Lifetime, Capacity factor; Nuclear decommissioning, long-term waste storage, and fuel costs)	Complete
Testing across countries	Full testing across countries	Complete
Scheduled Retirement of Coal	Done based on global data set at the national level (data are taken from Power Plant Tracker)	Complete
Cost-Based Early Retirement PPAs	Implemented	Complete
Comparison with other models	We implemented fossil PPA percentage for the ‘sclerotic’ power sector option when fossil fuel PPAs are present	Complete
Why the improvement?	Compare new and old power sector models to other power sector models	Done for EPM
	Assess and discuss differences between the ‘old’ and ‘new’ model – i.e., why is new better	Partially implemented
Individual country master-plans.	The model now allows exogenous investment/capacity to be input in the manual Inputs tab	Complete

3.1.8 Caveats

There are some notable caveats/limitations to CPAT, given its largely reduced form approach and its mid-term (to 2035) horizon. Sections of this document could also complement this

section by presenting the upgrades made to CPAT since the last review and outlining desired upgrades, known issues, and valuable analyses not completed.

3.1.8.1 Policy modeling

CPAT abstracts from the possibility of:

- **Designing complex policy packages**, including a **combination of instruments** (e.g., ETS, carbon tax, and offsets) and accounting for **mitigation actions** in the baseline scenario (beyond those already captured in recently observed fuel use/price data and known carbon pricing mechanisms). However, policy combinations can be done sequentially — analyze one policy and use this outcome as the new baseline for the next policy, etc. In the same vein, CPAT does not account for **international linkages across countries or emissions leakage**, which prevents explicit analysis of the implications of border carbon adjustments which are receiving increased attention.
- **Differences in fuel price responsiveness** may vary across countries with the structure of the energy system and regulations on energy prices or emission rates. Nonetheless, this latter default can be easily adjusted in individual country analysis. In addition, **feedback from carbon pricing**, like the impact of carbon pricing reform on commodity prices or interest rates which could be feedback to affect emission reductions, cannot be easily designed in an Excel-based tool.
- **Non-linear responses to significant policy changes**, such as rapid adoption of carbon capture and storage (CCS) technologies (deployed in the power and industry sectors) or even direct air capture.
- **Upward sloping fuel supply curves and changes in international fuel prices** that might result from simultaneous climate or energy price reform in large countries. CPAT is parameterized to behave like the mid-point of the broader modeling literature. Although many models account for these factors, no big difference is observed, given the relatively flat supply curves for coal.
- **Applying different coverage levels across sector groups**. CPAT allows the user to select the sectors and fuels to be considered for policy implementation:
 - For new policies, the coverage is binary, whether they are included or not.
 - Whenever the user defines exemptions for fuels or sectors and determines a phaseout period for those exemptions, the coverage can be fractional during that period.
 - For existing policies, instead, the coverage is mostly fractional, and it is currently computed as an average of the fuel demand covered across sector groups or fuel types.

3.1.8.2 Prices

When it comes to prices, CPAT does not model:

- **Upward sloping fuel supply curves and changes in international fuel prices** that might result from simultaneous climate or energy price reform in large countries—parameter values are, however, chosen such that the results from the model are broadly consistent with those from far more detailed energy models that, to varying degrees, account for these sorts of factors (see Section 3.8.3).
- **Institutional setup driving prices.** In CPAT, energy demand responds to prices in the private sector, although the institutional setup could, in some markets, prevent prices from determining supply and demand.

3.1.8.3 Emissions

The following limitations and constraints exist when computing the emissions:

- **In the current version of CPAT, international linkages across countries or emissions leakage are not factored in.** This prevents explicit analysis (in the first public version) of the implications of border carbon adjustments which are receiving increased attention.
- **Energy related N₂O emissions are calibrated on CO₂ emissions preventing the independence of one from the other.**
- In the case of LULUCF CO₂ emissions, **a condition to model the sink activity can create an irreversible state of a positive sink** (more absorptions than emissions). Even if the previous year's emissions (the year before the base year)B are negative, there is no possibility of returning to a negative sink.

3.1.8.4 Energy use (all energy sectors)

A first important caveat, common to all of our approaches, lies in the fact that the **autonomous efficiency improvement and time trend of consumer preferences and technology are treated in the same way.** In other words, it is implicitly assumed that the time trend of consumer preferences and technology is not varying. However, it can be subject to changes over time. For instance, technology can get more or less energy intensive as it changes.

3.1.8.5 Power sector

The two different power models in CPAT have different strengths and weaknesses. For ‘off-the-shelf’ use, we recommend using the average of the two models. We recommend the techno-economic (‘engineer’) power model specified with detailed modeling choices and input parameters for more tailored use.

The **elasticity-based power model** is responsive to *relative* price changes but not absolute prices. It does not explicitly model the capital stock, so it cannot distinguish between short-run capacity factor differences and long run capital stock changes. Thus, changes in generation for fixed capacity stock generation types may be too fast. It may also model unrealistic reductions in generation from renewables if their price were to increase relative to other options. Conversely, changes in generation for dispatchable types may be insufficiently responsive to price. The model could produce outcomes that are not physically realistic.

The **techno-economic ‘engineer’ power** model has the following caveats:

- **Investment behavior in state-owned power sectors responds to the carbon tax as a shadow price of carbon for government investment**, i.e., we assume state plans respond as well as the private sector.
- **The power maximum retirement rate for coal is set to 80%**.
- **Estimates of national capacity by generation type across time.** Since no such dataset exists globally, CPAT’s current approach relies on its own estimates. Fossil capacity collected from the EIA is scaled using independently estimated shares.
- **In CPAT, the investment decision is not fully commercial** but assumes a quasi-least cost approach to meeting aggregate energy demand (and power demand).
- **Fiscal expenditures of government investment in power are not accounted for.** Such a feature is not implemented, partly because power investment is typically funded by customers even if financed by the government – so including it would raise consistency issues.
- **There could be a better assessment of flexibility** (and ease of implementing VRE) based on the capacity reserve.
- **Losses associated with round-trip efficiency** (i.e., the ratio between the power put in and the energy retrieved from storage) are currently **not accounted for in the current model**. Power storage consumes electricity and saves it to hand it then back to the grid. The higher the round-trip efficiency, the less energy is lost in the storage process.

3.1.8.6 Desirable upgrades, known issues, and useful analyses not completed: General

This section contains our assessment of upgrades that are desirable but were not able to be completed. **We do not propose to do all these upgrades and seek the reviewer’s opinions if any of them are must-haves before releasing CPAT to the broader community.**

Issue	Comment/Status
Emissions Factors from IIASA include process emissions and are then calibrated	The current approach to IIASA emissions factors (which, inappropriately, include process emissions) and then calibrating total emissions is unsatisfactory. Perhaps use detailed energy balances to determine weighted average CO2 Efs. Priority: low
A better methane model (and, more generally, better models outside the energy sectors) is needed	The IMF plans to upgrade the methane model.
Short and long-term elasticity distinctions not included	We now eliminated the distinction between the short and long run. However, we think this is important, particularly for residential power demand, which is inelastic in the short term. We intend to revisit this in 2.0.
Covid adjustment is ad hoc	The Covid adjustment for 2020 is unsatisfactory and may be partly a response to the lack of the short-term/long-term distinction (i.e., too high price elasticities in the short term). I am not sure we can improve it due to the asymmetric nature of the shock. However, it might be better to still go with differences from the outturn. It can be turned off.
Regulatory policy	The semantics of the shadow price of regulatory policy options and then the 70% effectiveness weighting is highly unclear
Time Trend is not backed by detailed research and only relates (notionally) to efficiency improvement rather than other components of the time trend	The current time trend includes energy efficiency (negative trend). Still, there are also positive trend components to the time trend (e.g., shifts in tastes toward SUVs) that may not be captured in the income elasticity. Could reestimate the model.
Income elasticity: how to get away from that? Is there a relationship with a CGE model, rather than using this, which can be crude?	It was not implemented. No plans to adjust this.

Issue	Comment/Status
A closer connection to sectoral GVA forecasting might be desirable	To be discussed further.

3.1.8.7 Power Sector Models

CPAT does not aim to replace models like EPM; thus, we have limited the upgrades.

Comment	Status
Power supply feebates are implemented in the engineering model. Power efficiency feebates are in the elasticity model. The elasticity model could be phased out	It would be better if both models would do both types of feebates. Currently, we recommend the ‘average’ of two models. Could move to engineer model as a recommendation.
Land area-related physical limits	No change has been implemented – No current plans.
Interest rates not applied to the construction period Part of the levelized cost is to do with the actual capacity factor (the fixed operation and maintenance), and this could drive retirement Do not calculate the capacity reserve margin explicitly	TBC No change has been implemented – No current plans. No change has been implemented – No current plans.
Do not use residual Load curves or representative days, as they are viewed as too complex for Excel We do not have resource curves; wind global wind costs are irrelevant. This is very significant for hydro, for example	No change has been implemented – No current plans. For hydro and nuclear we recommend using exogenous scale up. These default to no investment before 2030 and only allow investment after this point if the generation type is already present
Calibrate storage requirements at a regional level	No change has been implemented – No current plans.
Explicitly estimate ‘k’ in the logit model (how sharply the sigmoidal function cuts out more expensive options)	No change has been implemented – No current plans.

Comment	Status
Concerning State-Owned Enterprises (e.g., in Power Sector), we might want to make the investment/derisking decision explicit in these cases rather than relying on the carbon tax. That would reduce the effectiveness of a carbon tax but might be better communication of what MoFs need to do regarding the direction of SOEs.	Not currently implemented.

3.1.8.8 Remaining Known Bugs or Issues

A model as complex as CPAT has some ongoing issues. These are stated here and are, in most cases, minor.

Comment	Status
PPAs	PPAs only affect dispatch and so have limited effect in the long term. Probably not an issue, but it needs an investigation.
State-owned power markets; Investment decision	Currently, the investment decision is driven by the carbon price, representing a shadow price for investment appraisal. This needs to be flagged more strongly for regulated power markets either in the documentation or in CPAT, or an option to explicitly add/remove a shadow price for investment appraisal.
Bhutan and elasticity power model	Issue when in the elasticity model that the balances do not fully balance between energy consumption and energy supply and when exports or imports are substantial (e.g., in Bhutan).
Russia	Russia's results need to be confirmed.
Small Countries	There are some issues with a few smaller economies. See the appendix showing the country list working. We do not intend to remediate all countries due to data limitations.

3.1.9 Notation and Acronyms

A table summarizing the Notation used is available in each modeling section. This section describes dimensions and acronyms.

3.1.9.1 Dimensions

CPAT exists across multiple dimensions. Each will be given the following index notation in the same order as described below.

Variable	Index
Scenario ⁷	<i>o</i>
Country	<i>c</i>
UNFCCC emissions sector ⁸	<i>u</i>
Sector grouping ⁹	<i>g</i>
Sector	<i>s</i>
Fuel and generation type ¹⁰	<i>f</i>
Pollutant	<i>p</i>
Year ¹¹	<i>t</i>

That means that a typical variable might be defined as follows $x_{ocsf,t}$ – with x being specific to scenario, country, sector, fuel type, and time. Particular values for these general indices are indicated with capitals, for example, $o=B$ for baseline.

The codes corresponding to elements of the dimensions (for example, fuel types and sectors) are also defined in tables in the appendices.

3.1.9.2 Institutions

EIA Energy Information Administration

IEA International Energy Agency

IIASA International Institute for Applied Systems Analysis

IMF International Monetary Fund

IRENA International Renewable Energy Agency

JRC Joint Research Centre (institution of the European Union)

NREL National Renewable Energy Laboratory

OECD Organisation for Economic Co-operation and Development

⁷With $o=(B)$ for baseline; $o=(P)$ for policy e.g., B carbon tax.

⁸Used in the emissions accounting section. This category distinguishes between energy-related (E), (which includes power, transport, buildings, industry and other energy use), Industrial Processes and Product Use (I), Agriculture (A), Land Use, Land-Use Change and Forestry (L), Waste (W), and Other (O) emissions.

⁹For the aggregation of energy and emissions, sector groupings refer to buildings (i.e., B residential, services, and food & forestry) industry, transport, and power. Some other calculations have different aggregations. For prices, sector groupings refer to residential, industry including services, transport, and power; for elasticities, sector groupings refer to residential, industrial, services (including food & forestry), transport, and power.

¹⁰The following abbreviations for fuels considered are used in the documentation: Coal (COA), Natural gas (NGA) Oil (OIL), Nuclear (NUC), Wind (WND), Solar (SOL), Hydro (HYD), Other renewables (REN) and Biomass (BIO).

¹¹ t_0 represents the first year of model calculations, also known as the base year (as of the time of writing, 2019).

US EPA US Environmental Protection Agency

WBG World Bank Group

3.1.9.3 Abbreviations

CapEx Capital Expenditure

CCS Carbon Capture and Storage

CO₂ Carbon Dioxide

CPAT Climate Policy Assessment Tool

EF Emissions Factor

ETS Emission Trading System

EV Electric Vehicle

ftt Fuel Transformation

GDP Growth Domestic Product

GHG Greenhouse Gas

HIC High Income Countries

HP filter Hodrick-Prescott filter

LCOE Levelized Cost of Electricity

LIC Low Income Countries

LMIC Lower Middle-Income Countries

LPG Liquefied Petroleum Gas

LULUCF Land-use, Land-use Change, and Forestry

MAC Marginal Abatement Cost

MT Multi Scenario Tool, a spreadsheet that allows multiple-country and -policies use of CPAT

NDC National Determined Contribution

OBR Output-Based Rebating

OpEx Operating and Maintenance Expenditure

PM Particulate Matter

PPA Power Purchase Agreement

PV Present Value
R&D Research & Development
SCC Social Cost of Carbon
SLCP Short-Lived Climate Pollutants
UMIC Upper Middle-Income Countries
UNFCCC United Nations Framework Convention on Climate Change
VAT Value-Added Tax
VKT Vehicle Kilometers Traveled
VRE Variable Renewable Energy
WACC Weighted Average Cost of Capital

3.1.9.4 Fuels

BIO Biomass
COA Coal
HYD Hydropower
NGA Natural Gas
NUC Nuclear
OIL Oil
REN Other Renewables
SOL Solar
WND Wind

3.1.9.5 Units

GJ Gigajoule

GWh Gigawatt Hour

ktoe Kilo Tonne of Oil Equivalent

kW Kilowatt

kWh Kilowatt Hour

kWy Kilowatt Year (=365*24 kWh)

MMBtu Million British Thermal Unit

MW Megawatt

MWh Megawatt Hour

MWy Megawatt Year (=365*24 MWh)

tCO₂ Ton of CO₂ Equivalent

USD United States dollar

3.2 Fuel prices, taxes, and subsidies

3.2.1 Overview

At the time of writing, the base year for CPAT is 2019. The base year plus the next two years (2020 and 2021) are considered the ‘historical price years’ for CPAT. The algorithm for the historical price years and the future price years is different; we use historical price information in the historical price years and a forecast approach for the future price years.

Domestic price information for historical time periods comes from a dataset created by the IMF side of the joint WB-IMF team. We refer to this dataset as the ‘IMF dataset’. Information about this dataset is available from the IMF and is not part of this documentation. The user can supplement these data with specifically-sourced data (‘manual inputs’).

To forecast domestic prices, we also use projections of *international* fuel prices (for example, crude oil prices). These forecasts are created as an average of internationally recognized sources. The default is an average of IMF and WB projections, although other options are available if the user chooses. The user should however make sure that these sources are updated.

While the method used to build the data may change from the ‘historical price years’ to the years where fuel prices are forecasted, the identity to obtain retail prices p_{cgt} (for a given country c , sectors grouping g and fuel type f , during period t) remains the same: **Retail**

prices equal the supply price plus all relevant taxes. As for the latter, the different hierarchies, coverage, exemptions, and types of tax, require additional disaggregations. For instance, value added taxes may be paid on top of other taxes and fees, so it will be convenient to express the retail price identity as:

$$p_{\text{cgft}} = sp_{\text{cgft}} + \text{vat}_{\text{cgft}} + \text{txo}_{\text{cgft}}$$

where sp stands for the supply price, vat is the value added tax, and txo stands for the excise and all other taxes. Furthermore, txo acts as net additional taxes, as it corresponds to the addition of fixed or ad valorem taxes, consumer side subsidies, any existing carbon price xcp , as well as the new carbon price introduced by the policy ncp .

Note that the existing and new carbon prices may result from policies related either to carbon taxation or ETS permit prices, as it will be explained in upcoming sections.

The table below summarizes the process used to build the information for prices and subsidies for the historical years and the forecasted period. Additional information on each element can be found in the upcoming sections.

Table 3.13: Price Forecasting Summary

Variable Code	Variable Name	Historical years' source	How Price is Projected
sp	Supply Price	IMF dataset	Scaled according to international prices
vat	VAT payment	IMF dataset	VAR rate applied to supply price and excise and other taxes
xcp	Existing Carbon Price	From State and Trends of Carbon Pricing	<i>Options</i> Either a defined schedule of projections or base year carbon price plus defined growth rate
ncp	New Carbon Price	From dashboard	Calculated according to policy settings
fixtax	Fixed portion of excise and other taxes	IMF dataset	Computed as the average of the fixed portion observed during the historical years
fixsub	Fixed portion of consumer subsidies	IMF dataset	Computed as the average of the fixed portion of subsidies observed during the historical years
fts	Floating portion of taxes and subsidies	IMF dataset	Based on historical values, on evolution of the supply price, and on price control phaseout
txo	Excise and other taxes	IMF dataset	<i>Addition of forecasted components:</i> $\text{txo} = \text{fixtax} + \text{fixsub} + \text{fts} + \text{xcp} + \text{ncp}$
p	Retail Price	IMF dataset	<i>Addition of forecasted components:</i> $p = sp + \text{vat} + \text{txo}$

3.2.2 Notation

The table below presents the notations used in the section and the name of the variables to which they correspond. Note that the units are reported as input into CPAT, but further conversions are made to ensure that they match our calculations.

Notation	Variable	Unit
p	Retail price	US\$/Gj
P	Aggregate retail price	US\$/Gj
sp	Supply price	US\$/Gj
$fixsp$	Fixed portion of supply price	US\$/Gj
$fltsp$	Floating portion of supply price	US\$/Gj
ps	Producer-side subsidy	US\$/Gj
vat	Value added tax	US\$/Gj
txo	Excise and all other taxes	US\$/Gj
$fixtax$	Fixed portion of taxes	US\$/Gj
$fixsub$	Fixed portion of subsidies	US\$/Gj
$flts$	Floating portion of taxes and subsidies	US\$/Gj
gp	Global fuel price	US\$/bbl for oil, \$/ton for coal and \$/MMBtu for natural gas
ϕ_{PS}	Phase-out factor for producer-side subsidies	
ϕ_{CS}	Phase-out factor for consumer-side subsidies	
ϕ_{PC}	Phase-out factor for price controls	
pcc	Price control coefficient	
Δgp	Difference between current and previous global prices	
$\delta_{CT/ETS}$	Fix growth rate for existing carbon tax or existing ETS permit price	
xct	Existing carbon taxes	US\$/Gj
$xetsp$	Existing ETS permit prices	US\$/Gj
xcp	Existing carbon price	US\$/Gj
nct	New carbon tax	US\$/Gj
$netsp$	New ETS price	US\$/Gj
ncp	New carbon price	US\$/Gj
$nexc$	New excise tax (if applicable)	US\$/Gj
NCT	National price per ton of CO_2 under a carbon tax	US\$/ton of CO_2
$NETSP$	National price per ton of CO_2 under an ETS	US\$/ton of CO_2

Notation	Variable	Unit
ef	Emission factors	tCO ₂ e/ktoe
$\varphi_{\text{NCT/ETS}}$	Sector-fuel coverage for the new policies (Carbon tax or ETS)	%
F	Use of fuel	ktoe

Fuel prices are different for each combination of fuel type f , country c and ‘sector group’ g (for prices meaning Residential, Industrial-including-Services, Transport and Power). Within the sector group, prices are equal – although more granular sectoral exemptions mean that prices in the sector can differ.

3.2.3 Historical years: Sources of information

The IMF dataset on prices and subsidies includes data for supply costs, producer subsidies, VAT, excise and other taxes, consumer subsidies, and retail prices by country, sector group and fuel type. This dataset is, hence, at the core of the information for historical prices used in CPAT. Existing policies (carbon taxation or ETS permits) with information both in terms of carbon price levels as well as the fuel and sector coverage, complete the dataset for CPAT’s ‘historical price years’. A brief description of the price components used in CPAT is provided below:

Historical retail price: Included in the IMF data set. Rounding errors aside, it equals the sum of supply costs, VAT, and excise and other taxes.

Supply price: Included in the IMF data set. It is calculated as a weighted average of domestic extraction costs and international prices plus transport costs, where the weights refer to the proportion of the components that are domestically produced or imported. The supply price already considers the producer subsidy and the margin over international prices.

Producer Subsidy: Included in the IMF data set. Computed as total subsidy over total sales (for a given fuel).

Fixed portion of the supply price: Included in the IMF dataset. Constant parameter by fuel and sector representing the margin applied over international prices.

Floating portion of the supply price: Residual of the supply price not explained by the fixed portion nor the producer subsidies.

VAT payment: Computed by deducing the portion of the retail price that corresponds to VAT payment given a known country-or-sector-specific VAT rate.

Excise and other taxes: Computed as the gap between retail price and the addition of supply price and VAT payment. It includes the elements detailed below.

Existing Carbon Price: Sourced from *State and Trends of Carbon Pricing*.

New Carbon Price: User-defined. It is typically zero in the historical years.

Floating portion of tax (or subsidy): Computed as the portion of excise and other taxes unexplained by other components.

Fixed portion of tax (or subsidy): Computed as the unexplained portion of excise and other taxes as a result of price controls.

3.2.4 Forecasted years: Construction of data on prices and taxes

Retail price: Computed as the addition of the supply price, the excise and other taxes, and the VAT payment.

Supply price: Computed as the sum of the fixed and floating portions of the supply price, minus any remaining producer subsidies.

Producer Subsidy: Obtained by adjusting the producer subsidy observed in t-1 with the phase-out factor for producer subsidies. The latter is built based on user-defined parameters specifying the year in which the phase-out starts and the number of years for it to be completed.

Fixed portion of the supply price: Constant parameter computed as the average its value during the historical years.

Floating portion of the supply price: Floating portion observed in t-1 adjusted by the growth rate of the international prices for the respective fuel.

VAT payment: Obtained by applying the VAT rate over the VAT tax base. The latter is assumed to result from the sum of the supply price and the excise and other taxes.

Excise and other taxes: Computed as the sum of fixed and floating portions of taxes on consumption, plus the existing and new carbon or excise taxes introduced as part of the polity.

Existing Carbon Price: Resulting for already implemented carbon taxes or ETS permits and their prices, it is assumed that these policies are complemented by any new measure selected by the user. Thus, the price is assumed to be equal to the latest available observation, adjusted by the user-defined growth rate for the carbon tax:

$$xcp_{cgft} = xct_{cgf,t-1} * (1 + \delta_{CT}) + xetsp_{cgf,t-1} * (1 + \delta_{ETS})$$

with $xct_{cgf,t-1}$ and $xetsp_{cgf,t-1}$ representing the existing carbon taxes and ETS permit prices per energy unit, respectively. As part of the advanced options, CPAT allows the user to select a fix growth rate for each – the existing carbon tax and the existing ETS permit price. This is captured by the parameter δ in both cases.

New Carbon Price: It accounts for the price resulting from the implementation of new policies (carbon taxation or ETS permit prices), such that $nep_{cgft} = nct_{cgft} + netsp_{cgft}$, which can be further decomposed as:

$$nep_{cgft} = NCT_{ct} * ef_{cgf} * \varphi_{NCT,cgft} + NETSP_{ct} * ef_{cgf} * \varphi_{NETS,cgft}$$

where nct_{cgft} and $netsp_{cgft}$ stand for the new carbon tax per energy unit and the new ETS price per energy unit, respectively. In both cases, the value per energy unit is obtained by considering the national price per ton of CO2 (NCT_{ct} or $NETSP_{ct}$), and scaling it by the country-sector-fuel specific emission factors, ef_{cgf} , and the sector-fuel coverage for the new policies within the country in question ($\varphi_{NCT,cgft}$ and $\varphi_{NETS,cgft}$).

Among the options available, the user can select the sector or fuel that will be exempted from the policy implemented. This is already considered in the sector-fuel coverage φ . Moreover, such exemptions can be phased out according to user-defined parameters.

Note that both the existing and the new ETS permit prices per ton of CO2, $XETSP_{c,t}$ and $NETSP_{c,t}$ respectively, correspond to the **adjusted** values after the penalization. In other words, to the value comparable to the level of a carbon tax. For more information on this, refer to Section 3.9.3.

Floating portion of tax (or subsidy): Computed by adjusting its historical average with the fluctuation of the gap between the current supply price and its own historical average. Whenever price controls are in place and being phased out, the phase-out factor is multiplied to the result previously obtained.

Fixed portion of tax: Assumed to remain at the same level as its average during historical years.

Fixed portion of subsidy: Outstanding fixed portion of subsidy obtained after considering its average level during historical years and the phase-out factor for the correspondent year.

3.2.5 Price aggregation

For reporting purposes, it is convenient to have an aggregate price for each type of fuel within a country. This price, computed for each scenario, is obtained as a weighted average of the sector-specific retail prices, where the weights are given by the total use of fuel f in country c :

$$P_{cf,t} = \sum_g \frac{F_{cgf,t}}{\sum_g F_{cgf,t}} * p_{cgf,t}$$

where $P_{cf,t}$ is the aggregate price for fuel f in country c , $F_{cgf,t}$ is the use of fuel f in sector g within country c , and $\sum_g F_{cgf,t}$ is the aggregation of the fuel f use across all sectors in that country.

3.3 Fuel Consumption

3.3.1 Overview

CPAT's mitigation module is based on a fundamental model structure described in a recent IMF (2019) paper. Energy use responds to energy prices and real GDP (total real GDP, not per capita GDP). The price elasticity includes a 'usage' response (e.g., how much each car is used) and an 'energy efficiency' (e.g., how fuel efficient the car is) component. The fuel equation estimate fuel consumption in the different sector groupings of CPAT.

In what follows, we present the equation form and then specific cases in which the equation might be slightly transformed or in which we factor in additional technologies in accordance with the sector under consideration, that is Transport, Buildings, Industry, Other Energy Use and Electricity.

3.3.2 Notation

The table below presents the notations used in the section and the name of the variables to which they correspond. Note that the units are reported as they were input into CPAT, but further conversions are made to ensure that they match our calculations.

Notation	Variable	Unit
F	Use of fuel	ktoe
Y	Total real GDP	US\$
p	Retail price	US\$/Gj
α	Autonomous annual energy efficiency improvement	%
Ψ	Covid adjustment factor to energy demand	%
ϵ_Y	Forward-looking real GDP-elasticity of fuel demand	%
ϵ_U	Elasticity of usage of energy products and services	%
ϵ_F	Efficiency price elasticity	%
$\epsilon_{\text{bio},f}$	Substitution elasticity between the most cooking fuel used and biomass	US\$/Gj
Eff_f	Natural gas, LPG and kerosene efficiency	%
Eff_{bio}	Biomass efficiency	%

3.3.3 Fuel Consumption Dynamics

The fuel use for fuel type f and sector s can be related to the fuel use in the previous year as follows:

$$\frac{F_{\text{ocsf},t}}{F_{\text{ocsf},t-1}} = \left(\frac{1}{1+\alpha_{\text{sf}}}\right)^{1+\epsilon_{U,\text{csf}}} \Psi_{\text{ct}} \left(\frac{Y_{c,t}}{Y_{c,t-1}}\right)^{\epsilon_{Y,\text{csf}}} \left(\frac{p_{\text{ocsf},t}}{p_{\text{ocsf},t-1}}\right)^{\epsilon_{U,\text{csf}}} \left(\frac{p_{\text{ocsf},t}}{p_{\text{ocsf},t-1}}\right)^{\epsilon_{F,\text{csf}}(1+\epsilon_{U,\text{csf}})}$$

where the main components of the equation are F , the fuel usage in ktoe, Y , the total real GDP, the prices p as presented in Section 3.2, α , the autonomous annual energy efficiency improvement and, Ψ , a Covid adjustment factor to energy demand (see Section 3.3.4.4). Note that additional policies affecting the parameter α can be manually added.

Additional policy-induced efficiency gains pa by sector:	
Power	0%
Road vehicles	0%
Residential	0%
Industrial	0%
Feebates	0%

Figure 3.5: Dashboard: Additional policy-induced efficiency gains by sector

ϵ_Y denotes the forward-looking real GDP-elasticity of fuel demand for fuel f in sector g . It thus translates a 1% increase in total real GDP into a fuel demand increase. CPAT does not distinguish between the elasticity for real-GDP-per-capita and the elasticity for population.

ϵ_U , is the elasticity of usage of energy products and services (i.e.B for a 1% increase in prices, how much will total usage be affected in the same year).

Finally, ϵ_F denotes the efficiency price elasticity.

For more information on the elasticities and the autonomous annual energy efficiency improvement, see Section 3.3.5. The latter is set to 0.5% or 1%, depending on the sector.

The terms of the energy use equation represent:

- A **GDP effect** $\left(\frac{Y_{c,t}}{Y_{c,t-1}}\right)^{\epsilon_{Y,csf}}$
- A **price effect on usage** $\left(\frac{p_{ocsf,t}}{p_{ocsf,t-1}}\right)^{\epsilon_{U,csf}}$
- A **price effect on energy efficiency**, $\left(\frac{p_{ocsf,t}}{p_{ocsf,t-1}}\right)^{\epsilon_{F,csf}(1+\epsilon_{U,csf})}$

Both autonomous and price-driven efficiency components are subject to rebound effects by raising to the power of $(1 + \epsilon_U)$, where ϵ_U is negative.

Note that the term effect on energy efficiency is affected by the shadow price¹² in case non-pricing policy types are implemented, that is feebates and power feebates, energy efficiency regulations, vehicle fuel economy, residential and industrial efficiency regulations. In the equation, the shadow price only affects the efficiency margin and not the price effect since, for instance, an energy efficiency regulation does not aim to increase prices but increases the efficiency.

¹²A shadow price translates a non-pricing policy type into an explicit carbon price.

For simplicity, we assume that all the effects take place over the course of one year. In reality, some effects will take time, but CPAT abstracts from these effects. CPAT is more suited to anticipated and progressively phased policies over the medium term.

Energy use is aggregated into five main sector groupings: Transport, Buildings, Industry, Other Energy Use and Electricity demand.

3.3.4 Specific cases

Few specific cases slightly affect the energy use equation described above or the energy composition, that is:

- The breakdown of biofuels and existence of jet fuel in the transport sectors;
- Self-generated renewables in the building and industry sectors;
- The substitution between biomass and LPG/kerosene/natural gas in the residential sector;
- For the year 2020-21, energy use is calibrated with a Covid adjustment;
- Fuel transformation; and
- Other energy use sector.

3.3.4.1 Biofuels and jet fuel

In the transport sector, for road transport only, biomass is further broken down into Bioethanol, Biodiesel and Other Biofuels. In addition, domestic aviation jet fuel is a fuel type not seen in other sectors.

3.3.4.2 Self-generated renewables

When aggregating energy use at the sector level, power generated outside of the power sector, that is self-generated renewables, is also accounted for. The energy use equation is the same as the one presented above, and the price used is that of solar energy.

3.3.4.3 Biomass substitution in the residential sector

When aggregating energy used, an option to account for **leakage into biomass** in the residential sector is available.

If this option is turned on, a percent change of the most used cooking fuel (i.e., natural gas, LPG or kerosene) is transferred to biomass. In other words, the relative price change in the most used cooking fuel results in a percentage change in its consumption; this variation change is substituted by biomass. The latter is composed of the substitution elasticity between the

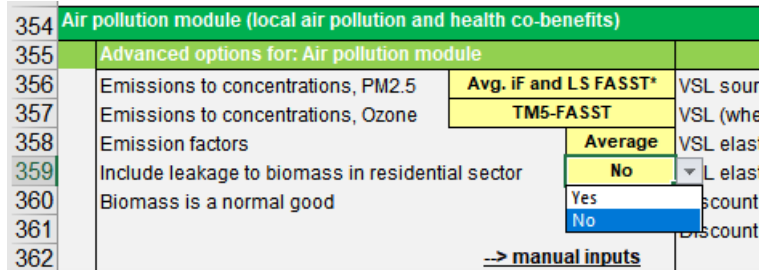


Figure 3.6: Sectors disaggregation in CPAT

most cooking fuel used and biomass ($\epsilon_{\text{bio},f}$), but also accounts for the relative efficiency between the fuels considered, that is only natural gas, LPG and kerosene ($f = \text{nga}, \text{lpg}$ and ker) and biomass (Eff_f and Eff_{bio} , respectively):

$$\epsilon_{\text{bio},f} * \frac{\text{Eff}_{\text{bio}}}{\text{Eff}_f}$$

The substitution elasticity between the most cooking fuel used and biomass, $\epsilon_{\text{bio},f}$, is 0.25 (see Section 3.3.5 for more information). The efficiency¹³ for each fuel is detailed in the table below:

Energy type	Efficiency
Natural gas	0.58
LPG	0.56
Kerosene	0.45
Biomass	0.20

The proportion of the natural gas transferred to biomass is thus dependent on the relative efficiency of representative stoves that are used. Therefore, for a 10% price change in, for instance, natural gas, 0.9% of natural gas consumption is shifted to biomass.

3.3.4.4 Calibration of overall energy use through Covid adjustment in 2020 and 2021

Due to the unprecedented global economic shock induced by the Covid-19, the energy consumption factor makes an ad hoc adjustment to the model and is calibrated using emissions outturn as the overall numeration in 2020 and 2021.

This sets baseline 2020 emissions to equal estimates for most countries and applies a GDP-linked scalar adjustment for all other countries to match global emissions (difference in recent three-year average GDP growth vs 2020 growth rate times 1.4). For 2021, emissions are set

¹³Efficiency in the residential sector is retrieved from Malla and Timilsina (2014).

for very large emitters (US, China, India, EU) to a specific rebound vs 2019 emissions per the Global Carbon Project (2021), and to a scalar that results in -4.2% vs 2019 emissions for all other countries. Estimates can be found at the end of the tab ‘GHG’.

COVID adjustment for 2020-21 (manually inferred based on 2020-21 observed emissions)					
China		Actual	Target	Difference	Note
Energy CO2 emissions in 2019		10,160.4	9,945.7	2.2%	Adjusted for by changing emissions factors
Energy CO2 emissions in 2020		10,531.9	10,080.1	4.5%	Adjusted for using below COVID adjustments
Country 2021 vs. 2019 emissions		7.2%	5.5%	1.7%	Adjusted for using below COVID adjustments
Targets for energy CO2			COVID adjustments		
Code	Country	2020 (level)	2021 vs.2019 (change)	2020	2021
CHN	China	10,080	5.5%	0.55%	19.60%
USA	United States	4,576	-3.7%	-9.01%	17.95%
IND	India	2,170	4.4%	-6.67%	19.87%
RUS	Russia	1,403	-4.2%	-2.41%	27.19%
JPN	Japan	977	-4.2%	-16.17%	17.59%
IRN	Iran	631	-4.2%	0.72%	10.06%
DEU	Germanv	601	-4.2%	-11.53%	24.74%

Figure 3.7: Summary of Covid adjustment

3.3.4.5 Fuel transformation

In CPAT we transform balances into final energy consumption (buildings, industry, transport, other), power sector (part of energy transformation in balances) and fuel transformation. The fuel transformation sector (FTR) is determined as **the difference between primary and final energy consumption, subtracting Fuel Transformation in the power sector**. This residual is treated as an additional industrial sector called fuel transformation.

In addition, all oil products and natural gas are aggregated to avoid dealing with negative fuel consumption. The FTR, computed as a residual, is treated as an additional industrial sector called ‘transformation’. For the forecasted years, its consumption follows the main mitigation fuel equations.

3.3.4.6 Other energy use

The other energy use sector contains principally military fuel use. No carbon taxes are imposed in this sector.

3.3.5 Income and Price Elasticities of Demand

3.3.5.1 Overview

The current version of CPAT uses a derived set of elasticities based on Burke and Csereklyei (2016) using the relationship from Gertler et al. (2016)

3.3.5.2 Income elasticities

Income elasticities relate to general energy demand (electricity, transport, industry, services, residential and other).

Income elasticities of energy demand are selected based on a broad literature review, simplified, adjusted for development levels, and sense-checked to a large dataset of income elasticities and outputs of other models. There are 32 ‘base’ income elasticates in CPAT covering eight energy sources (coal; natural gas; gasoline; diesel; other oil products like LPG and kerosene; biomass; small-scale renewables like solar PV; and electricity) and four sectors (transport including road, rail, aviation and shipping; residential; heavy industries; and public and private services).

These are then sense-checked against a database of income elasticities collected by the authors, which covers over 250 studies 2,000 observations of income elasticities across countries. Next, these are each adjusted for income per capita of the country considered in each projection period (‘adjusted income elasticities’) to reflect the broad finding that income elasticities decline with development. Lastly, the elasticities are checked once more through model intercomparison: comparing the baseline projections from those of many other global, regional, and country-specific models. The process is described further below.

Income elasticities	Transport	Residential	Industries	Services
- coal	0.00	0.40	0.50	0.70
- natural gas	0.50	0.60	1.00	1.00
- gasoline	0.70	0.50	0.50	0.50
- diesel	0.60	0.50	0.50	0.50
- other oil	0.80	0.50	0.90	1.20
- biomass	0.00	0.10	0.10	0.10
- renewables	1.00	0.75	0.75	1.00
- electricity	1.20	0.75	0.75	1.10

Figure 3.8: Income elasticities: Base income elasticities of energy demand in CPA

Base income elasticities for sectors are selected based on Burke and Csereklyei (2016), which covers 132 countries from 1960-2010. Fuel-specific elasticities within sectors are then selected based on a literature review such that the weighted global average income elasticity across fuels is within one standard deviation of those found for sectors (left panel of Figure 3.5). Broadly, energy demand grows more quickly in services, industry, transport, and other sector than it does in the residential or agricultural sectors.

It is then further assumed that income elasticities have a reverse-U shape with respect to income levels. This relationship has been found by numerous studies (Gertler et al. (2016); Zhu et al. 2018; Liddle and Huntington (2020); Caron and Fally (2022)). This non-homothetic relationship between incomes and energy could be reflective of the rapid rise in ownership of key energy consuming assets like refrigerators, air conditioners, and vehicles whose ownership tends to binary in nature (e.g. households purchase one fridge but not additional fridges as they become wealthier; Gertler et al. (2016)). It could also reflect the Environmental

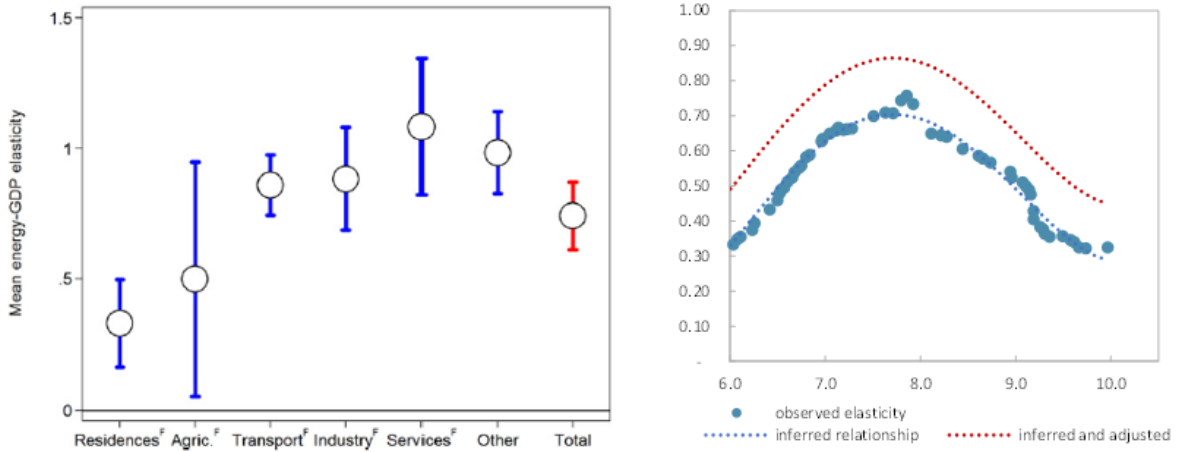


Figure 3.9: The relationship of fuel demand to GDP across countries by sector (left panel, mean estimated elasticities 1960-2010) and by development levels (right panel, un-adjusted and adjusted elasticities with respect to log GDP 1985-2010) – Source: left panel from Burke and Csereklyei (2016); right panel inferred from Gertler and others (2016), adjusted upwards to match the global average income elasticity for energy in left panel

Kuznets effect (as incomes increase economies reduce their environmental destruction by, for example, consuming fewer fossil fuels) (Saqib and Benhmad (2021)) or ‘dematerialization’ (richer countries tend to need fewer materials for marginal production and hence become more energy efficient).

The relationship between per capita incomes and energy demand is derived from Gertler et al. (2016) based on data cross-country analysis 1985-2010. This is then adjusted upwards such that the inferred global average income elasticity from this shape equals that found by Burke and Csereklyei (2016) (0.74, 2016) over the same time period (1960-2010). This adjustment is then applied to each base income elasticity’s base for each country over the projection period (varying with each year). The impact for selected fuel-sector pairs is shown in left panel below for per capita GDP and in the right panel for log GDP. Income elasticities jump up as countries graduate from being lower-income to a peak around lower-middle income status (at around \$3,000 per capita) and then asymptotically decline until reaching the developed country maximum (at around \$22,000 per capita).

Lastly, the results of these income elasticities on baseline energy consumption and emissions are then sense checked through a model inter-comparison. Overall, they allow for initially rapid accelerations in energy demand in developing countries (as households purchase energy-consuming goods like fridges, air conditioning units and cars) as well as broader structural change as countries increase the share of services in GDP and energy consumption.

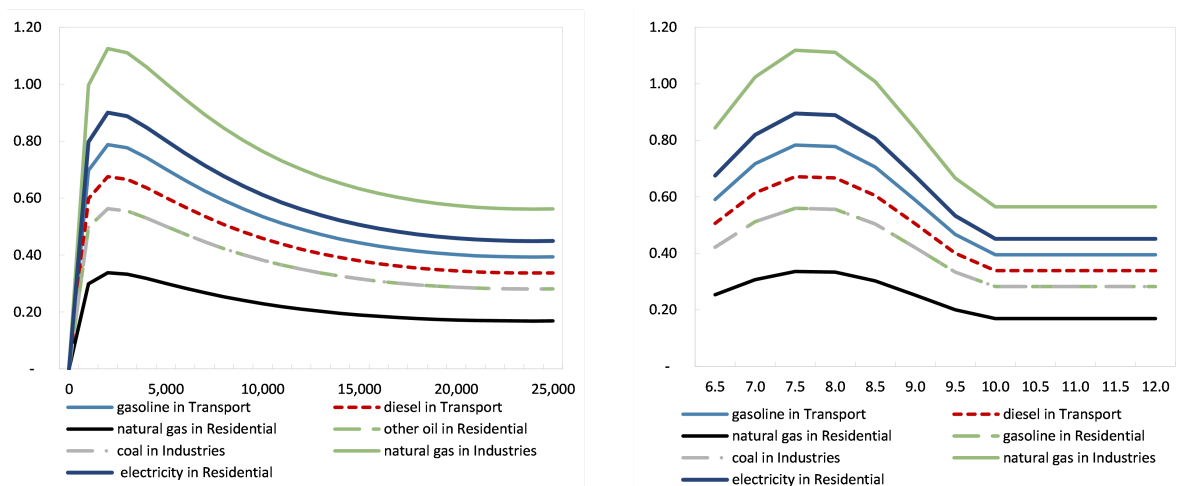


Figure 3.10: Per capita GDP adjusted income elasticities, selected fuels/sectors by GDP (left) and log GDP (right)– Source: IMF staff using Burke and Csereklyei (2016), Gertler and others (2016), and various other sources.

3.3.5.3 Price elasticities

Own-price elasticities of energy demand are parametrized using a similar approach to income elasticities. A major meta-study to estimate elasticities for fuels, which are then simplified and calibrated to allow for sectoral coverage, sense- and then finally sense checked to a large in-house dataset through model-intercomparison. These steps are described in turn.

Price elasticities in CPAT separated into two broad margins (see below). CPAT contains two types of price elasticities to distinguish between behavioral responses: the direct reduction in demand from reduced intensity of use from existing capital-consuming goods like vehicles (‘intensive margin’) and changes in the composition and scale of those goods (‘efficiency and extensive margin’). The two effects combined less the rebound effect (described later) correspond to the total price elasticity of demand, which is parametrized to the empirical literature¹⁴.

The initial source for price elasticities is a meta-study by Labandeira, Labeaga, and López-Otero (2017). This includes about 2,000 empirically estimated elasticities from 430 studies with broad global coverage of countries, seven fuels, and four sectors (refer to Table A for descriptive statistics). ‘Target’ estimates of elasticities for fuels and sectors are estimated, assuming that the base is the transport sector, plus deviations for the residential, industrial and services sectors (Table B)¹⁵. For any statistically insignificant values for fuels within sectoral regressions (natural gas in residential, for example), it is assumed that the difference between

¹⁴Empirical studies generally include rebound effects when estimating the total price elasticity of demand.

¹⁵Transport sector studies accord to the highest share of elasticity studies, mostly gasoline and diesel. For estimates see Tables A1-A4 in Labandeira, Labeaga, and López-Otero (2017).

sectoral and base elasticities equal that sectors' general elasticities multiplied by a scalar for all energy sources.

Additionally, there is evidence that price elasticities are slightly higher for developing countries (about Labandeira, Labeaga, and López-Otero (2017)). Price elasticities are therefore adjusted slightly upwards for developing countries (on the extensive margin) such that they are a similar magnitude higher than for developed countries.

Simple price elasticities (rounded to 1 decimal point) on both the intensive and extensive margin are then calibrated to those targets. As shown in Table C, when weighting for developed and developing countries' emissions, elasticities in CPAT are very similar (within 10%) to these target elasticities.

These, price elasticities are sense checked both against a large database of price elasticities (covering around 250 studies and 2,500 price elasticities), as well as through model intercomparison of CPAT results compared with those of other models. Both the baseline emissions projections and price responsiveness of emissions is broadly in line with that of other models, while median price elasticities are not significantly different for fuel-sector pairs collected across countries (though there is variation).

Lastly, all elasticities are long-term elasticities.

3.3.5.4 Rebound effect

When prices change, energy consumers also shift to more efficient energy-consuming goods. Marginal costs of fuel consumption are lower for more efficient goods (e.g.B each km travelled is cheaper for a vehicle with higher fuel economy), hence there is a corresponding increase in demand for those same fuels ('direct rebound effect'). As marginal costs of fuel consumption decline, consumers also increase the intensity of consumption of these capital goods (e.g.B travel more miles in vehicles).

The energy use equation outlined in Section 3.3 allows rebound effects, $(1 + \epsilon_U)$, to be captured and compared to econometric estimates of rebound. Broadly, these align with the empirical literature. More specifically, the rebound effect is defined as the product of the energy efficiency elasticity and the usage elasticity, $\epsilon_F * \epsilon_U$, as follows in the term affecting prices change:

$$\left(\frac{P_t}{P_{t-1}} \right)^{\epsilon_F + \epsilon_U + \epsilon_F * \epsilon_U}$$

With $\epsilon_F = \epsilon_U = -0.3$, the rebound effect represents 15.5% (i.e. the rebound effect reduces the total price elasticity by 15.5%). This result is lower, but seems more reasonable, than the estimates in a meta-analysis of 74 studies in Dimitropoulos, Oueslati, and Sintek (2018) (26-29% rebound effect, 2018).

The estimated leakage effects in residential natural gas (31%) are similar to those found in studies (20% to 30%, Haas and Biermayr (2000)).

Table A. Price elasticities of demand by sector, good, and country from meta study used for parametrization (long-term elasticities)

Sector	# observations	Mean elasticity	Proportion of 'total'
Residential	710	-0.62	1.4
Industrial	266	-0.51	1.2
Commercial	61	-0.72	1.6
Total (assumed transport)	839	-0.44	1.0
Good	# observations	Mean elasticity	Adjusted elasticity
Energy	376	-0.57	
Electricity	538	-0.51	-0.37
Natural gas	230	-0.57	-0.68
Gasoline	469	-0.53	-0.77
Diesel	136	-0.39	-0.44
Heating oil (assumed other oil)	44	-0.54	-0.19
Country	# observations	Mean elasticity	
Developed	1450	-0.52	
Developing	426	-0.55	
Net energy exporter	481	-0.51	
Net energy importer	1395	-0.53	

Source: Labandeira and others (2017)

Table B. 'Target' price elasticities based on empirical literature

	Base (assumed transport)	Residential	Industrial	Services	Simple average
Electricity	-0.37	-0.40	-0.40	-0.66	-0.46
Natural gas	-0.68	-0.76	-0.75	-1.01	-0.80
Gasoline	-0.77	-0.85	-0.85	-1.15	-0.91
Diesel	-0.44	-0.49	-1.18	-0.66	-0.69
Heating oil	-0.54	-0.59	-0.59	-0.79	-0.63
Simple average	-0.56	-0.62	-0.76	-0.85	-0.70

Source: IMF staff based on Labandeira and others (2017)

Table C. Actual total price elasticities used in CPAT for comparison (weighted by developed and developing country emissions)

	Base (assumed transport)	Residential	Industrial	Services	Simple average
Electricity	-0.34	-0.42	-0.42	-0.68	-0.47
Natural gas	-0.68	-0.70	-0.74	-1.04	-0.79
Gasoline	-0.77	-0.84	-0.84	-1.09	-0.88
Diesel	-0.50	-0.50	-1.11	-0.68	-0.70
Heating oil	-0.58	-0.58	-0.63	-0.80	-0.65
Simple average	-0.57	-0.61	-0.75	-0.86	-0.70

Source: IMF staff. Refer to Error! Reference source not found. for more detail on elasticities across margins.

Figure 3.11: Comparison of price elasticities

Table A. Price elasticities of demand by sector, good, and country from meta study used for parametrization (long-term elasticities)

<u>Sector</u>	# observations	Mean elasticity	Proportion of 'total'
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Gasoline	-0.77	-0.85	-0.85	-1.15	-0.91
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Heating oil	-0.54	-0.59	-0.59	-0.79	-0.63
Simple average	-0.56	-0.62	-0.76	-0.85	-0.70

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Gasoline	-0.77	-0.84	-0.84	-1.09	-0.88
Diesel	-0.50	-0.50	-1.11	-0.68	-0.70
Heating oil	-0.58	-0.58	-0.63	-0.80	-0.65
Simple average	-0.57	-0.61	-0.75	-0.86	-0.70

Source: IMF staff. Refer to Error! Reference source not found. for more detail on elasticities across margins.

Figure 3.12: Implied direct rebound effects from prices (endogenous efficiency improvements increasing demand for energy)

3.3.5.5 Cross-price elasticities

CPAT contains three substitution or cross-price elasticities to account for the risk that households that face increases in costs for residential heating and cooking fuels shift to informal fuels like biomass. This ‘leakage’ effect can have a negative impact on household air pollution and hence welfare, which is calculated by CPAT’s air pollution module. These cross-price elasticities (biomass with respect to LPG and kerosene, as well gasoline with respect to diesel) are parameterized to the same broad literature review.

Substitution elasticities	Transport	Residential	Industries	Services
Biomass wrt LPG in residential	na	0.25	na	na
Biomass wrt kerosene in residential	na	0.25	na	na
Gasoline wrt diesel	na	0.25	na	na

Figure 3.13: Cross-price elasticities of substitution in CPAT

3.3.5.6 Rates of technological change and exogenous rebound effects

The annual rate of exogenous technological change (that is, not induced by policies under consideration in CPAT) are set at between 0.5 and 1 percent per year for each fuel-sector pair.

Autonomous efficiency improvements in energy-consuming goods	Transport	Residential	Industries	Services
- coal	1.0%	0.5%	0.5%	0.5%
- natural gas	1.0%	1.0%	1.0%	1.0%
- oil	1.0%	0.5%	0.5%	0.5%
- biomass	1.0%	0.5%	0.5%	0.5%
- renewables	1.0%	0.5%	0.5%	0.5%
- electricity	1.0%	0.5%	0.5%	0.5%

Figure 3.14: Exogenous efficiency improvements in energy-consuming capital goods (cars, buildings, factories)

It should be noted that – as with efficiency induced endogenously by price changes – exogenous efficiency improvements reduce marginal costs of energy consumption, hence there is some rebound effect that partly offsets the reduction in demand from improved efficiency. A large literature exists that examines the rebound effect from efficiency improvements, with estimates varying significantly, from 0 to 300% (see for example Saunders et al. (2021)). In CPAT, this rebound from exogenous efficiency improvements depends on the fuel-sector pair and its corresponding intensive margin and efficiency, but broadly it is between 20% to 60% across fuels and sectors.

Rebound effect from autonomous efficiency improvements	Transport	Residential	Industries	Services
- coal	21%	30%	20%	30%
- natural gas	40%	60%	50%	60%
- oil products	21%	30%	20%	30%
- biomass	21%	30%	20%	30%
- renewables	40%	60%	50%	60%
- electricity	21%	30%	20%	30%

Figure 3.15: Rebound effect from exogenous efficiency improvements (% of emissions reduction reduced)

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3.4 Power sector models

The mitigation module has two models that can be used for the electricity sector: the elasticity-based model and the techno-economic (‘engineer’) model. The user can choose to use the elasticity, engineer model, or a simple average of the two models. We recommend the ‘average’ model for ‘off-the-shelf’ use of CPAT and the engineer model for more tailored usages and for non-marginal changes (like a high CO₂ tax policy). Before presenting the two models, it is essential to note that by default, prices and generation costs are applied to both the techno-economic (‘engineer’) and the elasticity-based power models. The main differences are as follows:

- **The ‘elasticity-based’ model** uses marginal increases in fuel prices and price elasticities to determine the shares of each generation type. It is simple, transparently parameterized, easily explainable, and easily deployable in an Excel spreadsheet model used in previous versions of CPAT and IMF tools.
- **The ‘engineer model’** explicitly models the capacity of different generation types, with capacity¹⁶ expanding to meet desired power demand. Power demand is a function of (price and GDP) elasticities, GDP change and end-user (residential and commercial/industrial) power prices. End user prices are taken from actual data with net subsidies constant and generation costs and carbon prices passed on to the users in default settings. Expected future capacity factors are assumed to match historical capacity factors in the base year (actual capacity factors for coal and gas generation are based on variable cost). Transmission losses and net electricity imports are modeled as a fixed quantity of total generation according to the energy balance data.
- The stock of assets in the power sector is governed by a stock-flow process of investment and retirement. Investment is a function of levelized cost, with a system penalty for the cost of integrating high levels of renewable penetration. The model allows the user to define a constraint on Variable Renewable Energy (VRE) scale up rate, reflecting a ‘linear’ type constraint. Additions to VRE additions are constrained to be a certain percentage of total generation (in gross additions, not net of retirements). Retirements are exponential (the reciprocal of the lifetime) except for coal, which has both scheduled retirement

¹⁶Capacity factors are assumed to be as in the base year (unless those capacity factors are outside of normal ranges, when default values are used)

based on country data, plus early retirement if the variable cost of coal generation (including carbon prices) exceeds the total cost of renewable-with-storage alternative (with quantities respecting the VRE scale-up constraint).

- Decisions changing the use of assets for power generation (dispatch) are also modelled, with renewables and nuclear dispatching ‘always run’ according to fixed capacity factors. Flexible capacity (gas and coal) is dispatched according to marginal price, to meet the residual power demand after always-run options, with a sigmoidal function of relative price. There is only one time period per year and a factor rewarding gas for increased flexibility is fitted to the historical data.
- The model is consistent with countries’ generation capacities and makes it possible to investigate the radically different power systems consistent with high carbon prices, while the empirical ‘elasticity-based’ model is valid only for more marginal changes.

In what follows, Section 3.4.1 defines power prices and generation costs, Section 3.4.2 describes the techno-economic model, and Section 3.4.3 the elasticity-based model. Finally, Section 3.4.4 presents the parameter choices of the power models.

3.4.1 Power prices and generation costs

This section describes the determination of generation costs and power prices in CPAT. These prices and generation costs are applied to the techno-economic (‘engineer’) and the elasticity-based power models. However, in the latter case, the user has an alternative option to use a simpler set of prices based on the original IMF board paper, which are not covered here.

3.4.1.1 Overview

Power generation costs have the following components:

- Variable (per kWh) operations and maintenance costs;
- Fixed (per MW) operations and maintenance costs;
- Decommissioning and waste disposal costs;
- Fuel cost before the introduction of the carbon pricing policy;
- Existing or new renewables subsidies;
- Existing or new carbon price or other policy (feebate, excise duty on electricity); and
- Systems cost of integration, modeled as short+long-term storage costs as a function of variable renewable energy (VRE; meaning wind+solar+other renewables, but not including hydro or biomass) share.

In addition, we impose an implicit price of coal relative to gas, reflecting unobserved environmental regulations on coal and the superior flexibility of gas. These aspects are not fully

captured in a model as simple as this. We calibrate this price on observed coal shares and future (IEA) projections (see Section 3.4.2.4).

End-user (industrial and residential) power prices additionally have the following components:

- Estimated transmission and distribution costs (different for industry and residential);
- Net historical subsidy or tax (estimated either via a price gap or via independent data if provided by the user);
- Any correction for under- or over-estimated transmission and distribution costs (exists only if we have concrete subsidy data);
- New carbon tax as imposed on the generation types and passed on to the end user; and
- Any electricity excise or rebate of the carbon price (Feebates/Output-based-rebating).

3.4.1.2 Notation

The tables below present the notations used in the section and the name of the variables to which they correspond. Note that the units are reported as they were input into CPAT, but further conversions are made to ensure that they match our calculations.

The first table gives overarching concepts relating to power generation.

Notation	Variable	Unit
F	Use of fuel	ktoe
g	Electricity generation	GWh
ν	Thermal efficiency	%
cf	Capacity factor	%
cap	Capacity	MW _y
PV	Present value of costs	
tic	Levelized total investment costs	US\$/kWh
wacc	Weighted Average Cost of Capital	%
lif	Lifetime	Years
dlf	Discounted lifetime	Years
Φ_{inv}	New investment expressed as a proportion of total existing capacity less retirements	%
gns	Generation shares	%

This table denotes variables used to calculate the levelized cost of investment types (and also, indirectly the power price).

Notation	Variable	Unit
fc	Projected unit fuel costs	US\$/kWh
opv	Variable costs for operating and maintenance (OpEx)	US\$/kWh
vc	Current variable costs	US\$/kWh
cax	Capital cost (CapEx)	US\$/kW
opf	Fixed costs for operating and maintenance (OpEx)	US\$/kW
tfc	Fixed OpEx	US\$/kW _y
sto	Storage cost	US\$/kWh
dtc	Decommissioning costs	US\$/kWh
ipc	Implicit price component for coal	US\$/kWh
pusRen	Per-unit renewable subsidies	US\$/kWh
LCOE	Levelized cost of electricity	US\$/kWh

This table denotes variables used to calculate the price of electricity.

Notation	Variable	Unit
hrp	Historical retail prices in the electricity sector	US\$/Gj
gnc	Current generation cost	US\$/kWh
fix	Amortized fixed costs	US\$/kWh
cax^{av}	Weighted average CapEx	US\$/kW
acc	Yearly amortization of capital costs	US\$/kWh
int	Interest costs	US\$/kWh
dec	Yearly amortization of decommissioning costs	US\$/kWh
sp_T	Supply power price determined in the engineer model	US\$/kWh
tmc	Transmission cost	US\$/kWh
mu^T	Markup used in the calculation of supply power prices	US\$/kWh
pex	Power excise	US\$/kWh
reb	Rebate	US\$/kWh
p^T	End-user power price (engineer model)	US\$/kWh

3.4.1.3 Power generation cost and price concepts

We use four different power generation cost/price concepts in CPAT:

- **Current Variable Costs:** For dispatch decisions the current variable costs are used (fuel and variable operations and maintenance).

- **Levelized Cost of Investment:** For forward looking (investment) decisions, a levelized and forward-looking cost approach adding all cost components is used. For example, one part is *forward-looking expectations* of future fuel and carbon costs.
- **Cost-recovery generation cost:** For estimating the total running cost of the power system, a cost-recovery generation cost is estimated. This includes current variable cost, running amortization of capital costs, plus average interest costs (and other components too). The cost-recovery generation cost by generation type is averaged and then transmission and distribution costs added to produce an overall estimate cost of generating and distributing electricity.
- **End user power prices** (residential and industrial): these are based on observed prices with an adjustment for changes due to cost changes or carbon pricing. The user can decide what proportion of changes to overall generation cost are passed on. The user can also choose to phase out estimated electricity subsidy.

3.4.1.4 Concept 1: Current variable costs

Variable costs are used in the dispatch decision directly between gas and coal.¹⁷

Current variable costs are defined as the sum of the following cost components:

$$vc_{ocft} = vop_{ocft} + fc_{ocft} + ip_{cft} = vop_{ocft} + \frac{p_{ocft}}{\nu_{cf}} + ip_{cft}$$

where:

- vop represents variable costs for operating and maintenance, that is variable OpEx in USD per kWh.
- fc denotes projected unit fuel costs before the introduction of the carbon pricing policy. These costs are calculated as the ratio of pre-tax prices (including producer-side subsidies) ps and thermal efficiency ν : $\frac{ps_{cft}}{\nu_{cf}}$. It is worth noting that no improvements in time is currently modeled. By default, fuel costs are considered as a moving average over a 5-year window. The option to use spot prices can be enabled in the dashboard:

Engineer Model Parameters:	
Dispatch	
k Parameter dispatch	2
Use Spot Fuel Prices in Engineer Power Model	No*
Maximum Coal Capacity Factor	90%
Maximum Gas Capacity Factor	90%
Minimum thermal efficiency	10.0%

Figure 3.16: Dashboard: Use Spot Fuel Prices in Engineer Power Model

¹⁷They are also components of the forward-looking levelized cost (see investment costs/LCOEs, later)

- ipc_{cft} denotes an implicit price component for coal. Note that this latter component could be turned off in the settings and not taken into account (for more information, see Section 3.4.2.4).

3.4.1.5 Concept 2: Levelized costs of generation (Forward-looking)

3.4.1.5.1 General approach

- LCOEs by generation type are estimated as a forward-looking (discounted cashflow) approach.
- Note these is different from the cost-recovery prices above as the cost-recovery approach uses an amortization of capital costs and running interest costs rather than discounting.
- Fuel and carbon costs in these LCOEs are forward-looking, meaning they are the discounted value of future cashflows assuming full confidence in the proposed policy and full foresight.

Forward-looking generation costs are defined using a levelized cost of electricity (LCOE) methodology, which relies on discounting at the appropriate discount rate. Levelized cost enables the comparison of different energy technologies with different characteristics (operating lifetime, capacity factor, construction cost, and time) on an equivalent basis. To the levelized cost, we add system integration costs. The levelized cost can be defined, in general, as the discounted sum of costs divided by the discounted sum of electricity produced. Let's assume that a generation technology produces power for N years, and we start counting at year zero (so there are N payments, with the first being t_0 and last being $t = N - 1$). We separate the components q (capital cost) of the levelized costs, which can be treated equivalently. For each component q of the levelized cost:

$$LCOE_q = \frac{PV_q}{\text{dem}} = \frac{\sum_{t=0}^{N-1} C_{q,t} e^{-rt}}{\sum_{t=0}^{N-1} g_t e^{-rt}}$$

where PV_q is the present value of costs, dem is the discounted power produced, g_t is the power produced at time t and $C_{q,t}$ is the q component of costs at time t , breaking down into the following components:

The full investment cost contains the following components:

- Capital expenditure
- Decommissioning (all generation types) and waste disposal cost (nuclear only)
- Variable OpEx
- Fixed OpEx
- Fuel Cost Before Carbon Price
- Marginal system cost of storage (see Section 3.4.2.5)
- Carbon Price
- Implicit cost of coal

Each of these components is calculated using the levelized cost formula above. Almost all components are either fixed or increasing/decreasing at a fixed rate. In that case we can use a geometric series approximation. See the appendices for a derivation.

The weighted average cost of capital (WACC) is by default income-dependent:

Income Level	WACC Assumed
HIC	0.075
UMIC	0.100
LMIC	0.125
LIC	0.150

The WACC can also be technology-dependent, i.e. it can be specified for each technology. At the same time, the WACC can be specified for the baseline and the policy scenario. Finally, the WACC can be defined globally by the user.

The levelized total investment costs is defined as:

$$tic_{P,cf} = \frac{vc_{P,cf} * cf_{cf} * dfc_{cf}}{cf_{cf} * dfc_{cf}} + fix_{cf}^{fl}$$

where dfc_{cf} is the discount factor $1 + wacc_{cf}^{t-t_0}$ and fix_{cf}^{fl} denotes the forward-looking levelized fixed costs, which is calculated as:

$$fix_{cf}^{fl} = \frac{cax_{cf}}{cf_{cf} * 365 * 24 * dl_{cf}} + \frac{dtc_{cf}}{cf_{cf} * 365 * 24 * dl_{cf}} + sto_{cf} + opf_{cf} + pusRen_{cf} + tmc_{fct}$$

where cax is the capital cost, dtc is the decommissioning total cost, sto is the cost of storage, f correspond to fixed costs for operating and maintenance, dl_{cf} denoting the discounted lifetime of each generation type f , $pusRen_{cf}$ reflects the per-unit renewable subsidies (if added), and tmc_{fct} the levelized transmission costs.

The Levelised Transmission Costs can be taken to a defined percentage in the dashboard:

134	Phase out coal and gas PPAs over n years?	5	If User-selected global WACC, what value?	7.5%
135	Calibration		Minimum WACC	1%
136	Use additional coal intangible cost	Yes*	Max coal/gas/hyd invsmnt as a percentage of total ge	10.0%
137	Manual Value for coal intangible cost (base year)	0	Max ore/nuc/bio invsmnt as a percentage of total ge	2.0%
138	Manual Value for coal intangible cost (2030)	0	If used, user-defined maximum Wind/Solar Scaleup	2.0%
139	Use Engineer Covid Adjustment (1=Yes 0=No)	0	% of Transmission costs to include in total levelise	100%

Electricity demand by sector (TWh) Total power systems costs by fuel (Engineer model) - incl storage for Power tipping points: new solar vs

Figure 3.17: Dashboard: percentage of transmission costs

In the dashboard, the following option allows the user to specify renewable subsidy under a baseline and policy scenarios:

After the introduction of the carbon pricing policy, the current total cost is:

08	B Power sector (Average* Model)		
09	<-- Advanced power sector options		
10	Elasticity Model Parameters:		
11	Elasticity model uses economy-wide or sectoral power	Economy-wide	Subsidies
12	Use old or new generation costs in elasticity model?	New*	Baseline renewable energy subsidy, \$/kwh nom \$ -
13	Use Elasticity Model Power Demand In Engineer Model	No*	Apply additional RE subsidy to hydroelectric power? No
14	Engineer Model Parameters:		Minimum (post subsidy) generation cost \$/kwh real \$ 0.01

Figure 3.18: Dashboard: Renewable subsidy (\$/kwh in nominal terms)

$$LCOE_{P,cft} = vc_{P,cft} + fx_{cft}^{\text{fl}}$$

$$\text{where } vc_{P,cft} = vc_{B,cft} + ncp_{cft}$$

3.4.1.5.2 LCOE methodology: Simplification

As mentioned in the main text:

$$LCOE_q = \frac{PV_q}{g} = \frac{\sum_{t=0}^{N-1} C_{q,t} e^{-rt}}{\sum_{t=0}^{N-1} g_t e^{-rt}}$$

where PV_q is the present value of costs, g is the discounted power produced, g_t is the power produced at time t and $C_{q,t}$ is the q component of costs at time t , breaking down into various components described in the above section.

There is a simplification in the case of **constant growth rates**. If at and after time n the residual components of the cashflow have consistent real (logarithmic) growth rate τ , i.e., $C_t = C_n e^{g(t-n)}$, then they form a geometric series, which can be summed analytically:

$$\begin{aligned} PV_{\text{ofCosts}} &= \sum_{t=0}^{n-1} C_t e^{-rt} + \sum_{t=n}^{N-1} C_n e^{-rn} (e^{\tau-r})^{t-n} \\ &= \sum_{t=0}^{n-1} C_t e^{-rt} + C_n e^{-rn} \sum_{t=n}^{N-1} (e^{\tau-r})^{t-n} \\ &= \sum_{t=0}^{n-1} C_t e^{-rt} + C_n e^{-rn} \sum_{t=0}^{N-n-1} (e^{\tau-r})^t \\ &= \sum_{t=0}^{n-1} C_t e^{-rt} + C_n e^{-rn} \frac{1-(e^{\tau-r})^{N-n}}{1-(e^{\tau-r})} \end{aligned}$$

If a component is fixed in time, i.e. $\tau = 0$ and $n = 0$, there's a further simplification:

$$\begin{aligned} PV_{\text{ofCosts}} &= C_n e^{-rn} \frac{1-(e^{\tau-r})^{N-n}}{1-(e^{\tau-r})} = C_0 \frac{1-e^{-rN}}{1-e^{-r}} \\ LCOE &= \frac{\sum_{t=0}^{N-1} C_t e^{-rt}}{\sum_{t=0}^{N-1} g_t e^{-rt}} = \frac{\sum_{t=0}^{N-1} C_0 e^t e^{-rt}}{\sum_{t=0}^{N-1} g_t e^{-rt}} = \frac{\sum_{t=0}^{N-1} C_0 (e^{\tau-r})^t}{\sum_{t=0}^{N-1} g_t e^{-rt}} = \frac{C_0 \frac{1-e^{-rN}}{1-e^{-r}}}{g_0 \frac{1-e^{-rN}}{1-e^{-r}}} = \frac{C_0}{g_0} \end{aligned}$$

3.4.1.6 Concept 3: Cost-recovery estimated total cost of generation

- Generation costs are modeled by component (CapEx, OpEx, Fuel costs etc). These are ‘cost recovery prices’ assuming amortization of CapEx, interest costs and so on.
- Weighted average generation costs are then augmented by global assumptions on transmission costs, to give estimated cost recovery price.
- Then the cost recovery price is compared to observed prices and the difference attributed to being a tax or subsidy (if no independent subsidy data is available) or an under/overestimated cost if independent (user entered) subsidy-data is available.
- For cost recovery, a weighted average CapEx of the capital stock is needed. For most generation types, the CapEx per MW is constant, but for renewable energies it declines rapidly so the weighted average invested amount per MW is estimated by taking a weighted average of the current running total with the cost of new additions.

The current generation cost before tax, $gnc_{B,cft}$, is thus composed of both variable and fixed costs:

$$gnc_{B,cft} = vc_{B,cft} + fix_{cft}$$

where vc denotes current variable costs (defined in an earlier section) and fix denotes amortized fixed costs.

Amortized fixed cost is the sum of the following elements:

$$fix_{B,cft} = acc_{cft} + int_{cft} + dec_{cft} + sto_{cft} + opf_{cft}$$

Where:

- acc is the yearly amortization of capital costs per kWh produced: $\frac{cax_{cft}^{av}}{cf*365*24*lif_f}$ with cax^{av} the weighted average CapEx, cf the assumed capacity factor and lif the lifetime for each fuel. The weighted average CapEx is defined as: $cax_{cf,t-1}^{av} * (1 - \Phi_{inv}) + cax_{cft} * \Phi_{inv}$ with cax_{cft} the CapEx and Φ_{inv} the new investment expressed as a proportion of total existing capacity less retirements. It is worth noting that the base year, t_0 , corresponds to cax_{cft} . Over time, the CapEx is not varying, except for renewables (for more information see Section 3.4.4.4).
- int is the interest costs per kWh produced, assuming a straight-line amortization of CapEx: $0.5 * \frac{cax_{cft}^{av} * wacc_{cf}}{cf_{cf} * 365 * 24}$ where $wacc$ is the WACC. The WACC can be adjusted according to different settings and both under a baseline and policy scenarios.
- dec denotes the yearly amortization of decommissioning costs¹⁸ per kWh produced: $\frac{dtc_{B,cft}}{cf_{B,cf} * 365 * 24 * lif_f}$ where dtc_{cft} denotes the decommissioning and transmission costs in USD per kW (for more information see Section 3.4.4.4).

¹⁸Decommissioning costs are not discounted.

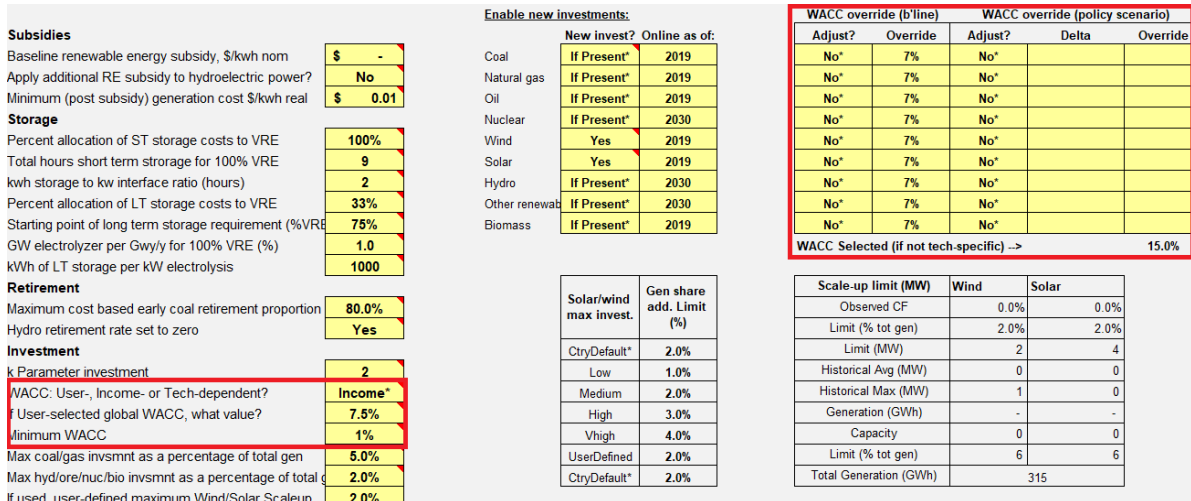


Figure 3.19: Dashboard: WACC Settings

- sto defines the weighted average storage cost of vintages, which corresponds to the marginal storage costs for renewable energies.
- Finally, opf represents fixed costs for operating and maintenance, that is fixed OpEx expressed in USD per kWh according to the capacity factor of each fuel: $\frac{tfc_{cft}}{365*24*cf_{cf}}$ where tfc is the fixed OpEx expressed in USD per kW.

3.4.1.7 Concept 4: End-user prices

- End-user prices are taken to be equal to current prices plus any change in underlying generation cost.
- *Observed* power prices are used as the basis of the demand model.
- *Changes* in generation costs (including those caused by carbon prices and any due to the phase-out of aforementioned subsidies) are assumed to be passed on to consumers (the proportion of pass-on defaults to 100% but can be altered.). If the parameter setting price controls is set to not one (could be 0, 0.25, 0.5, 0.75) then all price changes (from technology changes or carbon price) are diminished in the same proportion.

To estimate power prices (i.e. before the policy tax is introduced), the weighted current generation cost is calculated as follows:

$$gnc_{B,ct}^{av} = \sum_f gns_{B,cft} * gnc_{B,cft}$$

For each country, the weighted average of generation cost $gnc_{B,c}^{av}$ is calculated according to generation shares $gns_{B,cft}$ of each fuel f and their respective current generation cost $gnc_{B,cft}$.

In the engineer model, power prices are processed specifically in the residential and non-residential sector (i.e. industrial sector). The supply price in the technoeconomic model $sp_{B,cg}^T$ (where the index T holds for technoeconomic model) is determined in the residential and industrial sectors ($g = \text{Residential, Industrial}$) via a fixed positive increment corresponding to transmission cost (tmc) to the weighted average generation cost such as:

$$sp_{B,cg}^T = gnc_{B,ct}^{av} + tmc$$

An allowance of \$15/MWh and \$40/MWh was added to account for transmission and distribution costs for industrial and residential uses, respectively¹⁹.

A markup μ is then calculated specifically for residential and industrial electricity prices to equalize the starting year price (i.e. historical retail prices in the electricity sector, hrp_{cg}), as follows:

$$\mu_{B,cgt}^T = gnc_{B,ct}^{av} + tmc - hrp_{cg}$$

It is worth noting that when the markup is negative (i.e. retail prices are lower than modeled supply prices), the model captures a subsidy.

Carbon taxes are applied at the fuel-input stage to each generation. However, for the purposes of the overall generation cost, those costs are excluded as part of the generation cost average and averaged, and added on, separately. This is for the reason that doing this way allows us to calculate easily a needed rebate when rebating is employed.

The final residential and industrial end user power price in the technoeconomic power model, $p_{P,cg}^T$, is calculated as follows when a carbon price, ncp_{cg} , power excise, $pe_{P,cgt}$, a rebate, reb_{cg} , are introduced:

$$p_{P,cgt}^T = gnc_{B,ct}^{av} + ncp_{cgt} - reb_{P,cgt} + pe_{P,cgt} + tmc + \mu_{B,cgt}^T$$

At this stage two end-user power price settings are included:

- Output Based Rebating: the total carbon price is added to the generation types and then subtracted from overall power prices so that the overall policy is revenue-neutral.
- Electricity Excise: a per-kwh tax is *added* at the end-user stage

3.4.2 Techno-economic ('engineer') power model

3.4.2.1 Overview

Electricity is widely acknowledged to be critical to 'deep decarbonization' scenarios, in the sense that alternatives such as renewables primarily generate electricity instead of solid, liquid, or gaseous energy vectors. Deep decarbonization involves decarbonizing the existing power sector and electrifying sectors that currently use fossil fuels directly. Electrification will also

¹⁹See <https://www.iea.org/topics/energy-subsidies#methodology-and-assumptions>

involve expanding the power sector to accommodate the increased power demand from this shift in energy vector. Such a structural model is important for the following reasons:

- **Marginal versus radical.** Elasticity-based models are arguably best suited to price-based demand-side effects of marginal increases in fuel prices. They are less well suited to the non-marginal changes required for deep-decarbonization Paris-compliant scenarios.
- **Within bounds of equipment.** Power systems involve two significant sets of decisions: decisions that change the stock of power generation assets (investment and retirement) and decisions that change the use of those assets for electricity generation (dispatch). Without determining the capital stock, it is unclear that a particular choice of generation is consistent with the actual generation capacities of a specific country. An elasticity-based approach can produce non-physically realistic results (i.e., power dispatched that requires implicit investment rates faster than what is realistic).
- **Responsiveness to absolute levels of renewable costs.** Elasticity-based models can be unresponsive to actual levels of costs since it is based principally on the changes in cost.
- **Using accurate, referenced generation cost data.** The elasticity-based model used data that was at times not clearly referenced and not recently updated. For example, the percentage of non-fuel costs in total coal generation costs seems inconsistent between the spreadsheet and the published IMF paper. Neither are directly referenced against currently published costs.
- **Renewables costs are rapidly changing,** and it is helpful to model this explicitly.
- **The model should include, and the outcomes depend on, carbon price-dependent switching carbon prices for generation and investment.** It's helpful to know the 'switching cost' (for example, between coal and gas) in terms of the dispatch decision and the investment decision as a valuable marker of required carbon taxes to begin decarbonization.
- **Modeling the new reality.** According to Bloomberg New Energy Finance data, newly built renewables have already achieved cost-parity with newly built fossil fuel plants in many parts of the world. Consequently, the near future is likely to look very different from the past, even without any policy-led acceleration of the deployment of renewables. Indeed, the recent deployment of renewables has tended to surprise on the upside (e.g., actual deployment has tended to outpace IEA projections). It's unclear whether an elasticity-based model can fully capture these rapidly changing dynamics.

Summary of algorithm

As mentioned previously, the model has four types of prices:

- **Current Variable Costs:** For dispatch decisions, the current variable costs are used (fuel and variable operations and maintenance).
- **Levelized Cost of Investment:** For forward-looking (investment) decisions, a levelized and forward-looking cost approach adding all cost components is used. For example, one part is *forward-looking expectations* of future fuel and carbon costs.

- **Cost-recovery generation cost:** For estimating the total running cost of the power system, a cost-recovery generation cost is calculated. This includes current variable cost, running amortization of capital costs, plus average interest costs (and other components too). The cost-recovery generation cost by generation type is averaged and then transmission and distribution costs are added to produce an overall estimated cost of generating and distributing electricity.
- **End user power prices** (residential and industrial): these are based on observed prices with an adjustment for changes due to cost changes or carbon pricing. The user can decide what proportion of changes to overall generation cost are passed on. The user can also choose to phase out the estimated electricity subsidy.

The outlines of the algorithm are as follows:

1. End-user prices and GDP changes drive power demand by CPAT sector. (Some components of these prices are lagged one year to avoid circularity as Excel uses sequential rather than optimizing logic.)
2. According to historical energy balance data, transmission losses, own use, and net exports are added as fixed proportions of aggregated power demand.
3. Current inflexible capacity (renewable, nuclear) are assumed to dispatch at historical capacity factors, and the remainder is allocated to coal and gas according to available capacity using a logit formula based on variable cost.
4. Old capacity is retired according to either to defined data on retirement schedules (coal) or an exponential process (other generation types), with cost-based early retirement also included and an option to schedule retirement of coal.
5. Aggregate new generation capacity is added to meet expected demand assuming historical capacity factors.
6. Renewables are assumed to require both short- and long-duration storage, with assumed piecewise-quadratic total storage requirements, implying piecewise-linear marginal storage requirements. These storage requirements are approximately modelled based on global technical models. These storage costs are added to generation costs for Variable Renewable generation types.
7. Needed additions to aggregate ‘effective’ capacity (i.e. additions to expected generation) are then allocated according to another logit formalism based on total levelized costs by generation type, with the cheapest generation types taking the main share of the investment.
8. Renewables also have a maximum scale-up rate, set by default to 2 percentage points of total generation for wind and solar additional-generation. This setting can be changed by the user. Needed capacity beyond the limits are reallocated to other generation types according to the logit proportions. If there is still an unmet need for generation (for example in a high-hydro situation where new hydro investment is prohibited), the model

will *in extremis* override VRE scaleup limits and the allowed investment types and invest in proportion to the current proportions of capacity in the system.

9. Capacities after retirement and new investment are passed forward as the starting point of the model for the next year.

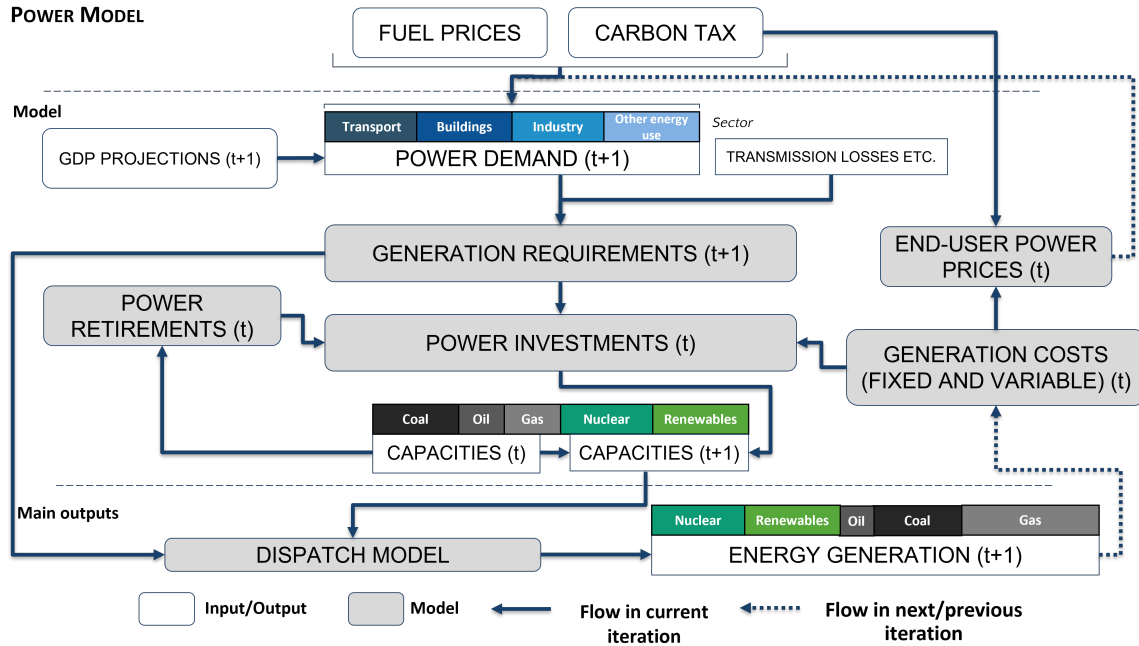


Figure 3.20: Techno-economic ('engineer') power model diagram

3.4.2.2 Notation

The table below presents the notations used in the section and the name of the variables to which they correspond. Note that the units are reported as they were input into CPAT, but further conversions are made to ensure that they match our calculations.

Notation	Variable	Unit
F	Use of fuel	ktoe
Y	Total real GDP	US\$
p	Retail price	US\$/Gj
α	Autonomous annual energy efficiency improvement	%
Ψ	Covid adjustment factor to energy demand	%
ϵ_Y	Forward-looking real GDP-elasticity of fuel demand	%
ϵ_U	Elasticity of usage of energy products and services	%

Notation	Variable	Unit
ϵ_F	Efficiency price elasticity	%
g	Electricity generation	GWh
E	Total quantity of power demanded by sector	GWh
net	Net exports (imports)	ktoe
eiu	Energy industry's own use	ktoe
Δ^{dif}	Transmission and statistical differences	ktoe
x	The variable x is used in the logit formula to alternatively represent investment, $x = \text{inv}$, or generation $x = \text{gen}$	GWh
K	Parameter adjusting the shape of the sigmoidal function. It determines the speed of transitioning between generation types with a different cost.	
$\text{reqgen}_{\text{COA}+\text{GAS}}$	Remaining generation allocated to coal and gas after nuclear, renewables, biomass and oil generation are subtracted	GWh
$\text{mingen}_{\text{COA},\text{GAS}}$	Minimum coal/gas needed assuming gas runs at maximum capacity	GWh
$\text{residualreqgen}_{\text{COA},\text{GAS}}$	residual power generation from coal and gas	GWh
$\text{maxCf}_{\text{GAS},\text{COA}}$	Maximum capacity for coal/gas	GWh
λ_f	Proportion of the residual generation (after the 'minimum coal' and minimum gas' allocation given limited capacity of the other) allocated to each of coal and gas	GWh
vc	Current variable costs	US\$/kWh
vc_{lc}	Lowest current variable costs between coal and natural gas	US\$/kWh
cf	Capacity factor	%
cap	Capacity	MW _y
ν	Thermal efficiency	%
$\tilde{\gamma}$	Generation shares before PPAs	%
γ	Generation shares after PPAs	%
ω	Percentage of PPAs	%
Ω	Downscaling factor if needed generation is different from that which is determined by the raw capacity factors	%
inv	Generation investments	MWh
ret	Generation retirements	MWh
lif	Lifetime	Years
rep_{COA}	Proportion of coal replacement	%
ζ	New investments permitted	MWh
ivp	Proportion of new investments	%
tic	Levelized total investment costs	US\$/kWh
tic_{lc}	Lowest levelized total investment costs between coal and natural gas	US\$/kWh
v	Variable renewable energy (VRE)	%

Notation	Variable	Unit
sst	Short-term storage	Hours
slt	Long-term storage	MW/MW, i.e. dimensionless units (%)

3.4.2.3 Power demand

The power demand, E_{cgt} , determines the total quantity of power demanded by sector. At present, our power demand is determined the same way as the equations outlined in Section 3.3.3, with fuel type equal to power (electricity) ($f = P$):

$$\frac{E_{\text{ocsf},t}}{E_{\text{ocsf},t-1}} = \left(\frac{1}{1+\alpha_{\text{sf}}}\right)^{1+\epsilon_{U,\text{sf}}} \Psi_{\text{ct}} \left(\frac{Y_{c,t}}{Y_{c,t-1}}\right)^{\epsilon_{G,\text{csf}}} \left(\frac{p_{\text{ocsf},t}}{p_{\text{ocsf},t-1}}\right)^{\epsilon_{U,\text{csf}}} \left(\frac{p_{\text{ocsf},t}}{p_{\text{ocsf},t-1}}\right)^{\epsilon_{F,\text{csf}}(1+\epsilon_{U,\text{csf}})}$$

where E is expressed in ktoe, Y is the total real GDP, α , the autonomous annual energy efficiency improvement. The prices p correspond to total (industrial and residential) power prices, as in Section 3.3.3). These prices respond to changes in weighted total generation cost, which is lagged by one year to avoid circularity issue.

A Covid adjustment factor to power demand Ψ can be taken into account (see Section 3.3.4.4 - note this is specifically calibrated for the engineer model). Note that additional policies affecting the parameter α can be manually added.

That power demand from the elasticity model can also be used (it is very similar, just not disaggregated by sector):

The total generation requirement (in ktoe), $g_{\text{oc},t}$, is therefore calculated as the sum of the total demand of all sectors augmented (subtracted) by the proportion – based on the base year – of net exports (imports), $\text{net}_{\text{oc},t_0}$, the energy industry’s own use, $\text{eiu}_{\text{oc},t_0}$, and transmission and statistical differences, $\Delta_{t_0}^{\text{dif}}$:

$$g_{\text{oc},t} = \sum_s E_{\text{ocs},t} * \left(1 + \text{net}_{\text{oc},t_0} + \text{eiu}_{c,t_0} + \Delta_{c,t_0}^{\text{dif}}\right)$$

3.4.2.4 Power supply

3.4.2.4.1 Logit function

Two different cost-based decisions are considered in the engineer model: the dispatch decision, determining how existing power plants are used, and new investment planning. In both of these decisions, the ‘multilogit’ function is used, with the probability of investment and dispatch of a technology increasing as a function of the price differential with alternatives. A parameter K adjusts the shape of the sigmoidal function that can be refined upon review of leading

Other assumptions		
Biomass is a normal good?		No
Include leakage to biomass in residential sector?		No
GDP growth adjustment		Base*
International energy prices adjustment		Base*
Baseline taxes are ad-valorem or fixed?		Fixed
Carbon tax policy announcement date		2022
Power sector revenues rebated		No*
National social cost of carbon (NSCC) source		Target*
Add non-climate Pigouvian taxes on top?		No*
Years to phase in non-climate Pigouvian tax?		5
Natural gas market assumption		Europe
Additional RE subsidy starting 2022. \$/kwh nom		0
Use Elasticity Model Power Demand In Engineer Model		No*
Minimum power price		0.01

Figure 3.21: Mitigation: Use Elasticity Model Power Demand In Engineer Model

power sector models employing a similar approach. They determine the speed of transitioning between generation types with a different cost. The K parameters are set with defaults set subjectively at 2 for both dispatch and investment, which we believe produces realistic results. This parameter can be adjusted in the dashboard:

The formula of the multilogit is as follows:

$$\frac{x_{\text{octf}}}{\sum_f x_{\text{octf}}} = \frac{e^{-K \cdot c}}{\sum_i e^{-K \cdot c}}$$

where $\frac{x_{\text{octf}}}{\sum_f x_{\text{octf}}}$ is the proportion (i.e. investment, $x = \text{inv}$, or generation $x = \text{gen}$) allocated to generation type f , and c_i is the relative cost of generation type f (i.e. the total levelized cost of electricity in the case of investment or variable costs i).

3.4.2.4.2 Dispatch decision

Dispatch decisions are based on a multi-step process.

The model first determines generation from nuclear, renewables, biomass and oil according to their capacity factor and the total supply required. In particular, renewables are assumed to produce power according to their installed capacity multiplied by historical capacity factors.

In the case of renewables, they are assumed to be non-dispatchable meaning their capacity factor is fixed. For nuclear, the low variable cost makes it economical always to run the plant when available. For biomass and oil, we simplify as we do not wish to model merit order decisions with many different fact (hourly peaking needs, environmental regulations etc).

Engineer Model Parameters:		Minimum (post subsidy) generation cost \$/kwh real	\$ 0.01
Dispatch		Storage	
k Parameter dispatch	2	Percent allocation of ST storage costs to VRE	100%
Use Spot Fuel Prices in Engineer Power Model	No*	Total hours short term storage for 100% VRE	5
Maximum Coal Capacity Factor	90%	kwh storage to kw interface ratio (hours)	2
Maximum Gas Capacity Factor	90%	Percent allocation of LT storage costs to VRE	33%
Minimum thermal efficiency	10.0%	Starting point of long term storage requirement (%VRE)	75%
Override capacity factor outside of:		GW electrolyzer per Gwy/y for 100% VRE (%)	1.0
Min (Sol/Wnd)	10.0%	kWh of LT storage per kW electrolysis	1000
Min(Others)	1.0%	Retirement	
Max(all)	100.0%	Maximum cost based early coal retirement proportion	80.0%
PPAs		Hydro retirement rate set to zero	Yes
Proportion of PPAs in coal and gas Generation	0.0%	Investment	
Phase out any coal and gas PPAs?	Yes*	k Parameter investment	2
Phase out of PPAs begins	2023	WACC: User-, Income- or Tech-dependent?	Income*
Phase out coal and gas PPAs over n years?	5	If User-selected global WACC, what value?	7.5%
Calibration		Minimum WACC	1%
Use additional coal intangible cost	Yes*	Max coal/gas invsmnt as a percentage of total gen	5.0%
Manual Value for coal intangible cost (base year)	0	Max hyd/ore/nuc/bio invsmnt as a percentage of total g	2.0%
Manual Value for coal intangible cost (2030)	0	If used, user-defined maximum Wind/Solar Scaleup	2.0%
Use Engineer Covid Adjustment (1=Yes 0=No)	0		

Figure 3.22: Dashboard: K parameters

Then, residual energy demand is determined by an explicit choice between coal and gas based on the variable cost of each (including the carbon tax). In other words, the remaining generation needed after nuclear, renewables, biomass and oil generation are subtracted, is allocated to coal and gas.

$$reqgen_{oc,COA+GAS,t} = g_{oc,t} - \sum_{f(RE,NUC)} cap_f * cf_f$$

First, we determine the minimum coal needed assuming gas runs at maximum capacity and vice versa for coal. The maximum capacity is by default set to 90%, but the user can adjust it in the dashboard:

For example, for coal:

$$mingen_{oc,COA,t} = reqgen_{oc,COAL+GAS,t} - cap_{GAS} * maxCf_{GAS}$$

Then, the remaining required generation after these minima are allocated to coal and natural gas, g_f , is determined based on their relative marginal costs, using the logit formulation:

$$\lambda_f = \frac{e^{-K_{dispatch} \cdot H_f}}{\sum_f e^{-K_{dispatch} \cdot H_f}}$$

where f is restricted to coal or natural gas and λ_f is the proportion of the residual generation (after the ‘minimum coal’ and minimum gas’ allocation given limited capacity of the other) allocated to each of coal and gas. The term H_g is the ratio $\frac{vc_{P,cft}}{vc_{P,ctt}}$, where the (marginal) variable

← Advanced mitigation options		
General assumptions		Add
First year of model calculations?	2019	Pow
Nominal results in real terms of which year?	2021	Roa
Use energy balances or (CPAT) energy consumption	Balances	es
Generate matrix of Energy Consumption Projections for	2019	ind
NDC submission	Latest*	Fee
Use 'world' (USA) or country-specific discount factors?	World	Adit
Sum all oil products in industrial transformation secto	Converted	Ene
Adjust Annex I country energy-related CO2 EFs to mat	Yes*	Veh
Adjust non-Annex I country energy-related CO2 EFs to	No	Res
Info: adjustment to EFs	1.00	Indu

Figure 3.23: Dashboard: Use energy balances or (CPAT) energy consumption data

cost is given by $vc_{P,cft}$ and $vc_{P,cft}^c$ is the variable cost of the lowest cost option between coal and natural gas, i.e. $f \in \{\text{coal}, \text{naturalgas}\}$, and K_g is the K parameter specific to generation.

Power generation for coal thus becomes:

$$g_{oc,COA,t} = \text{mingen}_{oc,COA,t} + \lambda_f * \text{residualreqgen}_{oc, \frac{COA}{GAS},t}$$

where residualreqgen denotes the residual power generation from coal and gas.

This procedure gives overall raw generation shares (assuming no PPAs), $\tilde{\gamma}_{ocf,t}$. It is worth noting that to the extent PPAs exist, a fixed capacity factor is used. Therefore, the latter is downscaled if the 'needed' coal and gas generation is less than what is implied by their default capacity factors. The total generation mix becomes:

$$\gamma_{ocf,t} = (1 - \omega_{ocf}) * \tilde{\gamma}_{ocf,t} + \omega_{ocf} * \Omega * (\text{cap}_{ocf} * CF_{cft})$$

where $\gamma_{ocf,t}$ is the generation share after PPAs ω denotes the percentage PPAs and Ω a downscaling factor if needed generation is different from that which is determined by the raw capacity factors.

3.4.2.4.3 Retirement and capacity needed

At the start of the analysis, the capital stock is based on electricity generation capacity data by fuel type from Enerdata. Required effective capacity is equal to expected generation capacity and is defined as capacity multiplied by the expected capacity factor — i.e., the investment is set such that the capacity is sufficient to cover expected peak demand, which is estimated using the power demand equation (see Section 3.4.1.2).

The economic system is expected to plan ahead a few years in advance so that investment takes place to meet the projected demand at the start of each year at the same time as retirement is modeled to happen. Capacity for the first year is thus determined based on IEA data.

For the following years, new capacity is thus equal to the old capacity, less retirements, and plus any new investments needed. The total required generation capacity is given by the expected power demand minus the generation capacity (last year's capacity less retirements):

$$g_{ocft} = g_{ocf,t-1} - \sum_f ret_{ocf,t-1} + inv_{ofc,t-1}$$

It is assumed that a generation dependent proportion, ret , of all generation assets retire each year, equal to the reciprocal of the average lifetime lif of that generation type.

$$ret_{ocft} = \frac{1}{lif} * cap_{ocft}$$

For coal, it is worth noting that planned retirement is adjusted based on the coal power plant tracker, which provides power plant data level for a number of countries. Therefore, based on these data, the retirement year of each power plant is determined and the capacity associated is determined from 2022 to 2050²⁰. When data do not exist, the above formula is used.

In addition to planned retirement, cost-based early retirement coal is also estimated as additional policies could accelerate retirement for coal power plants. In this respect, the model:

- First finds the maximum of coal that could be replaced by wind and solar. The maximum coal retirement is estimated as a fixed proportion (default 80%) of coal total effective capacity.
- Second, it compares the variable cost of coal with the total cost of wind and solar.
- Third, it calculates through a logit formula a proportion of the maximum coal replacement (depending on relative costs):

$$rep_{oc,coa,t} = 1 - \frac{e^{-K_i \cdot H_{r,COA}}}{\sum_f e^{-K_i \cdot H_{r,f}}}$$

where $H_{r,coa}$ is the ratio $\frac{vc_{oc,coa,t}}{vc_{ocft}^{lc}}$ and $H_{r,f}$ is the ratio $\frac{vc_{ocft}}{vc_{ocft}^{lc}}$ with $f \in \{\text{coal, solar, wind}\}$. The term $rep_{oc,COA,t}$ denotes the proportion of coal replacement.

In order to phase out coal only when coal prices are above renewables costs, we added a weighted indicator function to the logit formula.

Finally, the estimated proportion $rep_{c,coa,t}$ is multiplied by the maximum of coal retirement.

Therefore, the total retirement is equal to the sum of planned retirement and cost-based early retirement.

²⁰Power plants are removed if status is cancelled, shelved, mothballed.

3.4.2.4.4 Investment decision and non-VRE and VRE scale up limitations

Investment decisions are constrained by non-VRE and VRE limits and are based on two rounds:

- New investments permitted: A logit function capped by a VRE limit that spreads out investments across technologies based on the cheapest leveled costs.
- Allocated remaining capacity needed: A least-cost merit order algorithm allocates remaining capacity needed according to generation costs across technologies.
 - Logit function constrained by scale-up limits

Similarly as dispatch and retirement, new investment is spread out across the cheapest leveled possibilities, according to a multilogit formulation (with K parameter = 2):

$$\frac{ivp_{ocft}}{\sum_f ivp_{ocft}} = \zeta_{cft} * \frac{e^{-K_i \cdot H_i}}{\sum_i e^{-K_i \cdot H_i}}$$

Where: ζ_{cft} stands for new investments permitted in percentage. The user has the possibility to enable new investments (in MW). ivp_{cft} denotes the proportion of new investments K_i the K parameter specific to investment decisions. The term H_i is the ratio $\frac{tic_{P,cft}}{tic_{P,cft}^c}$, $tic_{P,cft}$ and $tic_{P,cft}^c$ define, respectively, the leveled investment cost and the lowest leveled investment cost across fuel types. It is important to note that renewables face a penalty at high levels (i.e., above 75% penetration) as an additional ‘storage systems cost’ could increase costs (see Section 3.4.2.5 on Long-term storage).

Different options are possible for whether new investments are permitted (iv^{new}):

- *If present* is the default option and allows new investments in the model if nameplate capacity > 0. Otherwise, no investment is accounted for.
- *Yes* allows the user to introduced planned investments, that is specifying a start year.
- *No* disables new investments.
- *Manual* allows the user to enter data. These data will override the data determined by the model and new capacity will be accounted for as: New Nameplate Investments (MW) = Capacity data entered by the user + Planned Retirement.

Maximum effective investments, iv^{\max} , are then capped by non-VRE and VRE limits (VRE):

$$iv_{ocft}^{\max} = g_{oc,t} * \zeta_{cft} * VRE_{cft}$$

Default non-VRE limits are set to 5% for coal and natural gas and 2% for hydro, oil, other renewables, nuclear and biomass. Default VRE limits are set to 2% (i.e. for wind and solar).

Enable new investments:		
	New invest?	Online as of:
Coal	If Present*	2019
Natural gas	Yes	2019
	No	
Oil	If Present*	2019
Nuclear	Manual	2030
Wind	Yes	2019
Solar	Yes	2019
Hydro	If Present*	2030
Other renewables	If Present*	2030
Biomass	If Present*	2019

Figure 3.24: Dashboard: Plan or enable new investment

CPAT allows the user to define non-VRE and VRE scale up rates. The rates reflect a ‘linear’ type constraint. It constrains generation in VRE additions to be a certain percentage of total generation (in gross additions, not net of retirements). For VRE rates, the following rates can be selected: Low (1%), Medium (2%), High (3%), Very High (4%), UserDefined and CountrySpecific (currently set to 2% – except for China 2.5%). The default is country specific.

Investment			Uncertainty adjustments:	
Parameter investment	2		International energy prices adjustment	Base*
WACC: User-, Income- or Tech-dependent?	Income*		GDP growth adjustment	Base*
If User-selected global WACC, what value?	10.0%		Price elasticities adjustment	Base*
Minimum WACC	1%		Income elasticities adjustment	Base*
Max coal/gas invsmnt as a percentage of total gen	5.0%		Adjust income elasticities for GDP levels?	Yes*
Max hyd/ore/nuc/bio invsmnt as a percentage of total gen	2.0%		Fiscal multipliers adjustment	Base*
If used, user-defined maximum Wind/Solar Scaleup rate	2.0%		Max RE scaleup rate	CtryDefault*
			Renewable cost decline rate	Medium*

- Least-cost merit order

The logit approach and the scale-up limitation determines ‘allocated’ investment. But there is still some needed investment that is not allocated. We use a least cost merit order approach to determine the currently ‘unallocated’ investment need.

The least cost algorithm ranks the generation types in terms of the cost and then use up all their available space (within the capacity limits) one by one, starting with the cheapest and so on.

First of all, the algorithm defines the **remaining unallocated investment need**. New effective investment before reallocation are defined as the minimum between maximum effective

Solar/wind max invest.	Gen share add. Limit (%)	Scale-up limit (MW)	Wind	Solar
CtryDefault*	2.0%	Observed CF	21.3%	16.4%
Low	1.0%	Limit (% tot gen)	2.0%	2.0%
Medium*	2.0%	Limit (MW)	17,412	22,536
High	3.0%	Historical Avg (MW)	2,658	3,502
Vhigh	4.0%	Historical Max (MW)	4,148	9,204
0	2.0%	Generation (GWh)	69,949	50,563
CtryDefault*	2.0%	Capacity	37,505	35,089
		Limit (% tot gen)	32,474	32,474
		Total Generation (GWh)	1,623,690	

Note: Scale up limits are an initial guide. The model will allocate residual needed investment after limits and primary reallocation in proportion to existing capacity. So for example a hydro dominated system will invest in more hydro once the 'allowed' limits are all used up.

Figure 3.25: Dashboard: Scale up rate specification for wind and solar

investments and new investments permitted in order to make sure investments cannot be superior to the maximum capacity. Therefore, this allows to determine the remaining investments needed, iv^{rem} :

$$iv_{\text{ocft}}^{\text{rem}} = iv_{\text{ocft}}^{\text{max}} - \min(iv_{\text{ocft}}^{\text{max}}, iv_{\text{ocft}}^{\text{new}})$$

Second, **generation costs are ranked from the cheapest to the most onerous across technologies** in order to allocate remaining capacity needed.

Third, remaining capacity are thus **allocated in a second round of investment** according to the cheapest technology in a cumulative way.

Finally, **total new investments equals investments permitted over the two rounds of investments**, that is before reallocation and after reallocation:

$$iv^{\text{tot}} = iv_{\text{ocft}}^{\text{new}} + iv_{\text{ocft}}^{\text{rem}}$$

3.4.2.4.5 Calibration and systems costs

Two calibrations are performed in the engineer power model, that is (1) a **calibration on the total electricity generation** and (2) an inferred value for systems cost, **calibrated on the share of coal**.

First, to ensure proper calibration of the engineer power model in 2020, a **COVID adjustment factor can be used to calibrate total electricity generation**. The latter, estimated by the model, is compared to observed data (IEA, 2020). The adjustment factor is calculated as the percentage difference between the estimated and observed data. Results per country can

be found in the tab ‘CovidAdjust’. For countries not covered by the IEA database, the factor adjustment is similar to the Covid adjustment on energy consumption (see Section 3.3.4.4). Importantly, in 2021, a rebound effect is introduced.

By default, the adjustment factor is set to 0. However, the user can rely on the adjustment factor by modifying the setting to 1 (see below). It should be mentioned that the lower and upper limits are set at 25%, which means that the factor adjustment cannot be less (more) than -25% (25%).

Calibration	
Use additional coal intangible cost	Yes*
Manual Value for coal intangible cost (base year)	0
Manual Value for coal intangible cost (2030)	0
Use Engineer Covid Adjustment (1=Yes 0=No)	0

Figure 3.26: Dashboard: Covid Adjustment

Second, **systems costs are currently inferred by using a calibration on the share of coal in the electricity generation.** This exercise is carried out using observed data in 2019 based on observed data from the IEA and consists of matching observed data for the coal share in the electricity generation. Systems costs are equivalent to an additional implicit price for coal, $imp_{c,coa,t}$. Inferred value for system costs are thus used for the years after 2019, with the exception of the year 2020. The latter is considered as exceptional because of the Covid shock. Therefore, the exercise is repeated for this year, as systems costs could be higher. IEA’s forecasts on the share of coal in total electricity generation for the year 2030 are also reported for information only.

	Goal Seek for 2019		Goal Seek for 2020		Goal Seek for 2030	
	Base actual	Base model	Base actual	Base model	Base actual	Base model
Generation (MWy)						
Coal	134,792	134,424	76,754	122,999	179,165	179,165
Natural gas	7,413	7,780	4,490	5,879	4,923	4,923
Oil	685	685	324	602	531	531
Nuclear	5,305	5,305	2,829	4,680	4,016	4,016
Wind	7,985	7,985	4,349	7,666	39,796	39,796
Solar	5,772	5,772	4,034	5,580	44,737	44,737
Hydro	19,680	19,680	10,983	19,680	19,680	19,680
Other renewables	305	305	105	298	231	231
Biomass	3,416	3,416	2,059	3,002	2,484	2,484
	185,353	185,353	105,927	170,386	295,562	295,562
Coal share	73%	73%	72%	72%	45%	61%
Distance	0.000		0.001		2.519	

The goal seek for the year 2030 is specific at the country level for Brazil, China, India, Russia and the US. For the other countries, the value is at the regional level. **The target is only informative for 2030.**

Figure 3.27: Dashboard: Covid Adjustment

For the years 2019 and 2020, the following steps are taken:

- The share of coal in total electricity generation is calculated for both the power model’s estimates and observed data from the IEA.

- To account for the difference between these two values, the “goal seek difference” is expressed as the following distance between estimated and observed coal share: $(coa_t^{est} - coa_t^{obs})^2$, where coa_t^{est} denotes the share of coal estimated by the power model and coa_t^{obs} represents the observed share of coal for $t \in \{2019, 2020\}$.
- As estimated coal share is often over-estimated compared to observed data, the goal seek difference is thus addressed by increasing prices for coal (i.e. an implicit price component) in order to reduce the difference between estimated and observed coal share. Only positive implicit price components are considered.

Results of additional implicit prices are reported in the tab ‘GoalSeekCoal’ for both 2019 and 2020. By default, CPAT uses the additional implicit prices. However, an option in the dashboard allows the user to turn this assumption off or to manually add the implicit price component.

Use additional coal intangible cost	No
Manual Value for coal intangible cost	Yes*
	No
	Manual

Figure 3.28: Dashboard: Coal share calibration

If the “Manual” option is selected, the user overrides the implicit price component with their choice.

Use additional coal intangible cost	Manual
Manual Value for coal intangible cost	0

Figure 3.29: Dashboard: Coal share calibration (manual)

3.4.2.5 Storage decision

CPAT has a simple model of electricity storage. The required storage consists of two elements, short and long-term. Both long and short-term storage is related to the proportion of renewable energy (VRE) generation as a percentage of total electricity generation. VRE includes wind and solar and other renewables but not hydro and biomass.

Because the model does not represent renewable energy generation profiles, relative quantification of balancing capabilities, or variability in demand, a “system integration cost” is imposed on higher shares of variable renewable energy (VRE). This cost is assumed to be an increasing function of VRE share. This additional cost forms part of the investment decision. The cost of integrating renewables is particularly significant at high levels (i.e. >50% by generation) of renewable penetration into an electricity mix. Against this background, two different types of storage are considered in the model:

- Short-term storage, which are costly per kWh but cheap per kW (e.g. batteries measured in kWh).
- Long-term storage, which are costly per kW but cheap per kWh (e.g. electrolysis and hydrogen tanks measured in kW).

For both types of storage there is an additional ‘hours’ ratio, measuring the ratio of battery capacity (kwh) to battery interface (kw), and electrolyzers (kw) to hydrogen storage (kwh). Each storage aspect is two-dimensional, meaning that every storage technology is determined by an ‘interface’ (kW) and a ‘storage quantity’ (kWh). The model measures storage according to one ‘numeraire’ and one ratio. For short-term storage, we measure the kWh and assume a standard 4-hour ratio between the kWh and kW in determining the costs. We calculate the kW for long-term storage and assume 1000 hours of storage per kW.

3.4.2.5.1 Short-term storage

Short-term storage in CPAT is satisfied by the batteries. Total storage needs are calculated in hours, which means kWh of storage per kW of average generation (not peak capacity).

The model uses rounded versions of a parameterization derived from global data (Bogdanov et al. (2019)). The model assumes that the total number of storage for a 100% VRE system is 9 hours, with a quadratic form. We fit the short-term storage needed (in hours) as a (conservative) quadratic function of the VRE. We allocate some percentage of this (currently 100%) to the costs of the power system itself. VRE, v , includes solar and wind but not hydro (other renewables are neglected). Short-term storage sst is measured in hours, i.e. kWh/(kWh/h). We also assume a ratio between the kWh of the storage and the kw interface. For conservatism (given our metric is in kWh), we use a low number (2 hours) for the ratio of kWh to kw:

$$sst = 9v^2$$

$$sst = 9v^2$$

By way of example, for a 50% VRE system, the hours needed are $9 * 0.5^2 = 2.25$ hours.

Therefore, the marginal storage needed is:

$$\frac{dsst}{dv} = 18v^2$$

The system has assumed to already have invested optimally in the existing storage at current VRE.

3.4.2.5.2 Long-term storage

CPAT also has a long-term storage model. Long-term storage is additional to short-term storage and is measured according to the cost of the interface (i.e., the electrolyzers rather than the cost of the storage tank). The interface is measured in units of KW. Therefore the proportion of long-term storage per kW of average generation is measured in dimensionless terms (kW per kW or %).

Long term storage slt costs are treated as effectively punitively costly (in contrast to short term storage), reflecting current costs and technological uncertainties. The long-term storage model assumes zero need for long-term storage below a VRE penetration of 75 percent, raising to 100 percent at a VRE of 100 percent. To this end, long-term storage is viewed as additional to short-term storage, and is needed for VRE over 75%.

Since batteries and hydrogen have other uses, we also have a parameter that determines the proportion of the short-term and long-term storage allocated to the electricity system. This is set to 100% for short-term storage and 33% for long-term storage. This parameter can be modified in the dashboard:

Storage	
Percent allocation of ST storage costs to VRE	100%
Total hours short term storage for 100% VRE	9
kwh storage to kw interface ratio (hours)	2
Percent allocation of LT storage costs to VRE	33%
Starting point of long term storage requirement (%VRE)	75%
GW electrolyzer per Gwy/y for 100% VRE (%)	1.0
kWh of LT storage per kW electrolysis	1000

Figure 3.30: Dashboard: Percent allocation of LT storage costs to VRE

Given its interseasonal storage and geographic independence, we focus on the costs of electrolyzers for storage. This storage cost is thus assumed as a long-term storage and is measured with the interface (i.e. electrolyzers) as the numeraire. It is given by the following quadratic function:

$$\text{slt} = \begin{cases} 0 & \text{for } v \leq 0.75 \\ \left(\frac{v-0.75}{1-0.75}\right)^2 & \text{for } v > 0.75 \end{cases}$$

Long term storage requirements are measured in MW/MW, i.e. dimensionless units (%). The marginal MW of electrolyzers required once VRE penetration reaches 75% is thus varying according to the derivative $2 * \frac{v-0.75}{(1-0.75)^2}$. The table below shows the results for different levels of VRE.

VRE penetration	Marginal MW of electrolyzers required
85%	2.5
90%	5.0
95%	7.5
100%	10.0

3.4.2.5.3 Levelized cost of storage

The levelized cost of the marginal quantity of storage needed to maintain required quantities of total storage is added to the investment costs for VRE. This means that the storage-inclusive cost of renewables can rise in time as renewable penetrations increase, even if the cost of renewables without storage is falling.

3.4.3 Elasticity model

3.4.3.1 Overview

The elasticity-based model is derived from an IMF spreadsheet tool, with a methodology described in IMF (2019). The CPAT mitigation module, and the IMF tool on which it is based, are primarily elasticity-based models, meaning that future fuel demand is dependent on projected total real GDP growth, and upon future energy prices, modified by mitigation policies such as carbon taxes. The power supply model is also based on elasticities, although it has a more complex structure than in other sectors. It separately models final power demand, and within that overall power demand the generation share of different generation types.

3.4.3.2 Notation

The table below presents the notations used in the section and the name of the variables to which they correspond. Note that the units are reported as they were input into CPAT, but further conversions are made to ensure that they match our calculations.

Notation	Variable	Unit
E	Total quantity of power demanded by sector	GWh
Y	Total real GDP	US\$
p	Retail price	US\$/Gj
α	Autonomous annual energy efficiency improvement	%
Ψ	Covid adjustment factor to energy demand	%
ϵ_Y	Forward-looking real GDP-elasticity of fuel demand	%
ϵ_U	Elasticity of usage of energy products and services	%

Notation	Variable	Unit
ϵ_F	Efficiency price elasticity	%
g	electricity generation	GWh
Φ	Production share	%
gnc^*	Total unit cost adjusted of thermal efficiency	US\$/kWh
$\epsilon_{\tilde{E}}$	Conditional own-price elasticity of generation from fuel f with respect to generation cost	%
δ^{add}	Additional share of electricity generation attributed to non-nuclear and non-hydro energy	%
TotExcess	Total surplus of nuclear and hydro power generation to be redistributed	%
F	Use of fuel	ktoe

3.4.3.3 Generation costs

Importantly, by default, the power generation costs are taken from the engineer model (i.e. levelized fixed cost plus current variable costs, but excluding intangible coal cost). However, this assumption can be modified and the cost model from the IMF board paper can, if wished, be selected in the dashboard. The methodology for these ‘old’ costs is given the IMF paper mentioned above.

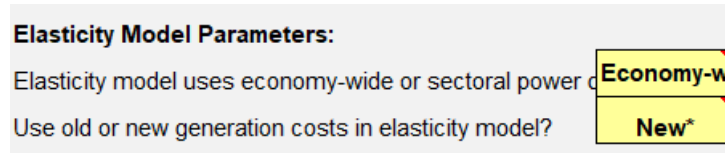


Figure 3.31: Dashboard: Use old or new generation costs in elasticity model

Renewable producer subsidies under a baseline scenario, as well as under the policy scenario, can be specified in the dashboard:

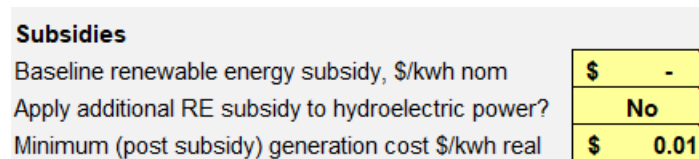


Figure 3.32: Dashboard: Renewable producer subsidies under a baseline scenario

3.4.3.4 Total power demand

As described above, power demand is determined by the energy use equation. As this is a total power demand, elasticities are averaged across all sectors. The autonomous efficiency improvements (or more especially, the annual generation productivity improvements) used across fuels are as follows:

Fuels	Change
Coal	0.5%
Natural gas	1.0%
Oil	0.5%
Nuclear	1.0%
Wind	5.0%
Solar	5.0%
Hydro	1.0%
Other renewables	5.0%
Biomass	1.0%

Productivity improvements at power plants reflect improvements in technical efficiency and gradual retirement of older, less efficient plants. Following the IMF Board Paper, for coal, annual average productivity growth is taken to be 0.5 percent based on IEA's data. For natural gas, nuclear, and hydro, there is likely a bit more room for productivity improvements and baseline annual growth rate of 1 percent is assumed. For renewables, a productivity growth rate of 5 percent is used (i.e., costs halve every 15 years).

For the base year, energy consumption is extracted from energy balances, expressed as total energy consumption net of fuel transformation and transportation. The index E denotes the sector Electricity.

For 2020, estimates are based on the previous year's data adjusted for a one-time exogenous shock, i.e., Covid (see Section 3.3.4.4).

$$\frac{E_{\text{oct}}}{E_{\text{oc},t-1}} = (1 + \alpha)^{-(1+\epsilon_U)} (1 + 0.5 * \Psi_{\text{ct}}) \left(\frac{p_{\text{cEt}}}{p_{\text{cE},t-1}} \right)^{\epsilon_{U,\text{cE}}} \left(\frac{p_{\text{cEt}}}{p_{\text{cE},t-1}} \right)^{\epsilon_{F,\text{cE}}} \left(\frac{Y_{\text{ct}}}{Y_{\text{c},t-1}} \right)^{\epsilon_{G,\text{cE}}}$$

In the elasticity model, half the usual Covid adjustment is employed as power demand does not fall as far as other energy types.

3.4.3.5 Total power supply

Power generation fuels potentially include coal, natural gas, oil, nuclear, hydro, biomass wind, solar and other renewables.

Similar to the engineer model, total demand is scaled to generation (which includes additionally transmission losses, energy industry own use and transmission losses). The total production of electricity, g_{oct} , is driven by the total power demand multiplied by the ratio of generation to demand in the base year.

$$g_{\text{oct}} = E_{\text{oct}} * \frac{g_{\text{oc},t_0}}{E_{\text{oc},t_0}}$$

For the base year, total electricity generation is based on observed energy balance data, which is the sum of all electricity generation from each fuel f .

The elasticity model provides two types of information when it comes to forecast generation of each type of fuel: the electricity output and the primary energy used for electricity production for each technology.

The electricity output from technology f is defined as the production share multiplied the total production. The production share, Φ_{ocft} is derived from observed data and is defined as the ratio between the observed electricity output from fuel f and the total production, that is $\frac{g_{\text{ocft}}}{g_{\text{oct}}}$. The production share is assumed to be fixed until 2020. After this date, to accommodate flexible assumptions for the degree of substitution among fuels, the share of fuel f in generation is defined as:

$$\Phi_{\text{ocft}} = \Phi_{\text{ocf},t-1} \left(\frac{\text{gnc}_{\text{ocft}}^*}{\text{gnc}_{\text{ocf},t-1}^*} \right)^{\epsilon_{\tilde{E}}} + \frac{\Phi_{\text{ocf},t-1} \sum_{i \neq f} \left[1 - \frac{\text{gnc}_{\text{ocit}}^*}{\text{gnc}_{\text{oci},t-1}^*} \right]^{\epsilon_{\tilde{E}}}}{\sum_{j \neq f} \Phi_{\text{ocj},t-1}}$$

where i and j are bound variables ranging over the same range as f (i.e., OIL, NGA, COA, NUC, WND, SOL, BIO, REN, HYD). In addition, $\text{gnc}_{\text{ocft}}^*$ denotes the total unit cost adjusted of thermal efficiency and $\epsilon_{\tilde{E}} < 0$ is the conditional own-price elasticity of generation from fuel f with respect to generation cost. Conditional (indicated by *tilde*) here means the elasticity reflects the percent reduction in use of fuel f due to switching from that fuel to other generation fuels, per one-percent increase in generation cost for fuel f , holding total electricity generation fixed. Generation cost elasticities are larger than corresponding fuel price elasticities as an incremental increase in fuel and non-fuel generation costs has a bigger impact than an incremental increase in fuel costs alone.

From the above equation, fuel f 's generation share decreases in own generation cost. It also increases in the generation cost of fuel $i \neq f$, where the increase in fuel f 's generation share is

the reduced share fuel i (i.e., Φ_{oct} times the term in square brackets) multiplied by the (initial) share of fuel f in generation from all fuel alternatives to i (i.e., $\frac{\Phi_{\text{oct},t-1}}{\sum_{f \neq i} \Phi_{\text{oct},t-1}}$):

NB: The actual equation in CPAT also reflects that nuclear and hydro should normally not grow beyond current levels. Therefore the model reallocates any excess growth for nuclear and hydro to other generation types. The equation above thus becomes:

$$\Phi_{\text{oct}} = \Phi_{\text{oct},t-1} \left(\frac{\text{gnc}_{\text{oct}}^*}{\text{gnc}_{\text{oct},t-1}^*} \right)^{\epsilon_{\bar{E}}} + \frac{\Phi_{\text{oct},t-1} \sum_{f \neq i} [1 - \iota_{\text{cft}}] \epsilon_{\bar{E}}}{\sum_{f \neq i} \Phi_{\text{oct},t-1}} * \delta^{\text{add}}$$

where $\iota_{\text{cft}} = \frac{\text{gnc}_{\text{oct}}^*}{\text{gnc}_{\text{oct},t-1}^*}$ and $\delta^{\text{add}} = \frac{\text{TotExcess}_{\text{oc,NUC+HYD},t}}{(1 - \Phi_{\text{oc,HYD},t} - \Phi_{\text{oc,NUC},t})}$

The energy used of each technology f in electricity production

Similarly, to electricity output, the base year corresponds to observed data, with the exception of wind, hydropower, solar and other renewables which are equal to electricity output. Therefore, for the following years, the energy used in electricity production is expressed as follows:

$$F_{\text{oct}} = E_{\text{oct}} * \left(\frac{1}{1 + \alpha_f} \right)^t \frac{F_{\text{oct},0}}{E_{\text{oct},0}}$$

The fuel use is equal to the electricity generated multiplied by an efficiency improvement over time α_f specific to the generation type f .

3.4.4 Power data sources and parameter choices

3.4.4.1 Overview

3.4.4.1.1 Sources

The section presents the data sources and the methodology to estimate the different characteristics of the power sector. In particular, is it first important to present the data and explain how consistency is ensured across the different data sources. The remainder of the section focuses on the methodology employed to estimate the power sector characteristics.

In the mitigation module, and in particular in the power sector, CPAT relies on several characteristics presented in the section below, along with their definition.

The table below presents the different data sources used to estimate power plant characteristics.

Table 3-7: Power characteristics and data sources

	Unit	Breyer	EIA	Enerdata	IEA&NEA	IRENA	JRC	NREL
CapEx	USD/kW	X	X	X	X	X	X	X
Fixed OpEx	USD/kW	X	X				X	X
Variable OpEx	USD/kWh	X	X					X
Lifetime	Years				X		X	
Capacity Factor	Percentage				X	X		X
Efficiency	Percentage		X		X			X
LCOE	USD/kWh							Own computation

Figure 3.33: Data mapping and description of data sources

As presented above, CPAT relies on various data sources which provide project-based data, that is:

- Stefanides (2021): The IRENA Renewable Cost Database contains cost and performance data for around 17 000 renewable power generation projects across the world with a total capacity of more than 1,770 GW.
- Lorenczik et al. (2020): The database covers 243 plants in 24 countries.
- EIA (EIA, 2021): Data were collected on the status of existing electric generating plants and projects scheduled for initial commercial operation within 5 or 10 years in the United States and Puerto Rico.
- Enerdata: The tool provides data power generation assets in around 150 countries throughout the world based on 7800 operating projects or projects under development.
- Zucker (2018): Based on confidential, project-based European data from 2015, the authors provide forecast estimates of investment costs.
- Bogdanov et al. (2019): This study bases its global estimations on various above-mentioned sources. In particular, the authors rely mainly on IEA&NEA for renewable data and BNEF for non-renewable data to forecast some characteristics. The authors provide data for the years 2015, 2020, 2025, 2030, 2035, 2040, 2045 and 2050.
- NREL: Cole, Frazier, and Augustine (2021) and Augustine and Blair (2021) provide historical as well as forecast data for utility-scale battery storage costs in the United-States. The former article's data and estimates are based on a survey of 18 studies, including sources mentioned above. Cole, Frazier, and Augustine (2021) update their work on a yearly basis. Cole, Frazier, and Augustine (2021) is the latest update. The latter study based their projection costs on BNEF data, which provide learning rates and deployment projections for utility-scale battery. Another advantage of relying on BNEF data lies in the provision of data on component of batteries.

3.4.4.1.2 Data approach for the power prices and ‘Engineer’ power model

The power models have important data requirements. There are two main types of data sources: first (method one), we have components that are directly from, or derived from, energy consumption data and energy capacity data; second (method two), we have components that come from studies.

Two crucial quantities use a combination of data sources: thermal efficiency and capacity factor.

Method 1: Energy Consumption, capacity data, and derived data

There are three primary energy consumption datasets used: electricity generation (in GWh), by generation type, fuel use (in ktoe), and electrical capacity (in MW). Before beginning, all three energy sources are converted to a consistent unit, MW, equivalent to MWy per year.

Thermal efficiency is calculated thus:

$$\nu_{cf} = \frac{g_{cf,t_0}}{F_{cEf,t_0}}$$

For coal, natural gas, oil, nuclear, and biomass, where F_{ocEf,t_0} is the fuel f used for the generation of electricity g_{ocf,t_0} ²¹, in the base year, baseline scenario. For solar, wind, hydro, and other renewables, efficiency is set by convention to 1. As mentioned before, we use Net Calorific Values exclusively.

If efficiency is less than a certain level, currently set to be 10%, we use the best data from studies rather than derived efficiencies. Note the efficiencies are not ‘floored’ in this case but instead set to be equal to the study data.

Capacity data are taken from EIA, except for fossil fuel types which are taken from the EIA all-fossil average and then descaled using estimated proportions calculated by CPAT from other sources.

Capacity factors are derived in a similar way

$$cf_{cf} = \frac{g_{cf,t_0}}{cap_{cf,t_0}}$$

These data are used in CPAT unless they are outside specific ranges set in the dashboard.

Method 2: Components derived from studies

To compute cost, specific disaggregated prices and other components (e.g., lifetime) data by technology and sometimes by country are used. Input data are derived as averages of EIA, IEA & NEA, IRENA, JRC (EU), Bodganov, et al., and NREL data.

²¹Note that the electricity sector is denoted by E.

These averages are made by country, region and world, with selected study data chosen by country, region then world according to data availability. Note that the asia region does not include China, Japan and (South) Korea, because of widely different costs compared to the regional average.

The table below provides an overview of the different sources, methodology unit and coverage for each data type employed in the engineer power model:

Data section	Methodology	Unit	Data level	Data source
Main parameters	Simple averages of available data points are computed. In the first stage, in order not to overweight one data source over another, the averages are calculated by data source, as a data source may provide different data at a given time and for the same technology because data are project-based. In a second step, the calculation of averages is deployed in the following order of priority: by country, by CPAT region, and globally.	CapEx, variable and fixed OpEx are in USD/kW	Global	IRENA; IEA&NEA; EIA; Enerdata; JRC; Bogdanov et al. (2019); NREL
		Capacity Factor, WACC and efficiency are in percentage	Regional	
		Total life-time is in years	Country	

Data section	Methodology	Unit	Data level	Data source
Evolution of CapEx	In the case of wind and solar, we use the learning curve method to forecast global CAPEX from 2023 to 2050. We use capacity projections from the IEA Stated Policy (STEPS) and Net Zero (NZE) scenarios, then experience Parameters extracted from Way et al., 2022 . Following the work of JRC (see Ioannis Tsiropoulos, Dalius Tarvydas, and Andreas Zucker 2018), the learning curve method to forecast CAPEX for renewable energies other than wind and solar from 2023 to 2040 is applied to each CPAT region, China, Japan, Korea and worldwide. The other technologies, i.e. coal, oil, natural gas, and nuclear, are not subject to a learning rate nor to different scenarios and are assumed to be constant over time.	Index (base year: 2019)	Global	Emerdate, IEA, Way et al. 2022, IRENA, Breyer, JRC and NREL
Decommissioning & transmission costs	Decommissioning and transmission costs are based on estimates provided by several data sources. The average is computed and then transformed to be expressed as percentage of CapEx. NB: Transmission costs in % of CapEx are not currently used in CPAT. Transmission costs rely on the IEA.	Percentage of CapEx; \$/kwhe	Global	Decommissioning costs (Raimi, 2017; OECD&NEA, 2016; Duke Energy Corporation) & Transmission costs (Andrade & Baldick, 2017; IEA)
Installed capacity	CPAT algorithm is used to calculate the shares of installed capacity for coal oil and gas.	Installed capacity in MW	Country	IEA

Data section	Methodology	Unit	Data level	Data source
Planned retirement	Based on the power plant data level, the retirement year of each power plant is determined and the capacity associated is determined from 2000 to 2050. Note: Power plants are removed if status = cancelled, shelved, mothballed.	Capacity in MW		Coal Power Plant tracker
Battery Storage age	Data are directly retrieved from the LUT model and interpolated when missing.	Battery: Global CapEx, variable and fixed OpEx are in USD/kWh Battery interface: CapEx and fixed OpEx are in USD/kW and variable OPEX in USD/kWh		LUT model (Bogdanov et al., 2019)

Data section	Methodology	Unit	Data level source
Energy recosts	The estimation of energy recosts (Non-fuel Levelized Generation Cost) are based on the main parameters. The costs estimates are only computed for solar and wind.	Water Electrolysis: CapEx and fixed OpEx are in USD/kW and variable OPEX in USD/kWh Lifetime in years	2017/CWHIRENA; IEA&NEA; EIA; Enerdata; JRC; Bogdanov et al. (2019); NREL
Maximum and average MW capacity increase	The methodology is derived from Energy GP. The data reflect the year 2020.	Max and Average Capacity and Total Capacity are in MW	Country GlobalIRENA

Data section	Methodology	Unit	Data level	Data source
		Average and Max growth rate are in percentage	Country	

3.4.4.2 Description and definition of the variables

Capital costs are overnight, that is excluding interest payments during the construction time. **Overnight cost** designates the cost of a construction project if no interest rates are incurred during the construction time.

In the power sector, **thermal efficiency (or heat rate)** expresses the fraction of heat that becomes useful work. In other words, the amount of energy input that is transformed into work output can be computed through the thermal efficiency: $\varphi = \frac{W}{Q_I}$. Thermal efficiency is comprised between 0 and 100%. For instance, if 200 joules of thermal energy are input (Q_I), and the engine transforms this energy into 80 joules, the efficiency rate is 40%. In the United-States, the heat rate is widely spread and is expressed in British Thermal Units (BTU). One BTU is equivalent to roughly 1055 joules and 2.93E-4 kWh.



Figure 3.34: Data mapping and description of data sources

There are two ways of calculating thermal efficiency, that is in **net or gross calorific value**. Calorific value is an essential parameter to specify the energetic content of different materials. **Net calorific value (or low heating value)** subtracts the heat of vaporization of the water from the gross calorific value, while the **gross calorific value (or high heating value)** is the total amount of heat produced from the complete combustion of a unit of a substance. It is essential to verify whether the efficiency is net or gross because the difference can be about 5% to 6% of the gross value for solid and liquid fuels, and about 10% for natural gas.

For instance, in a gas power plant, let's say that to produce 1kWh of electricity, 3kWh of natural gas in gross calorific value (GCV) is necessary. The net calorific value (NCV) can be derived from the gross calorific value by using a factor of 0.9 (Eurostat et al., 2004). Consequently, in NCV, 2.7kWh are necessary to produce 1kWh. The thermal efficiency is therefore equivalent to $\frac{1}{3} = 33\%$ in GCV and $\frac{1}{2.7} = 37\%$ in NCV or, equivalently, the thermal efficiency in GVC corresponds to the thermal efficiency in NVC to which the conversion rate is applied: $37\% \times 0.9 = 33\%$. The conversion rate fluctuates with the fuel used but also the technology used. Finally, the heat rate is often expressed in British thermal units (BTU) per net kWh generated. To express the efficiency of a generator or power plant as a percentage, it is essential to divide the equivalent BTU content of a kWh of electricity (3,412 BTU) by the heat rate.

The **capacity factor** measures the frequency of operation of a power plant during a given period. It is expressed as a percentage and is calculated by dividing the unit's actual power output by the maximum possible output. This ratio indicates how much of a unit's capacity is being used.

3.4.4.3 Consistency across data sources

The simple average of the data sources is used to construct our dataset of electricity sector characteristics. Nevertheless, faced with different approaches, we first analyze the underlying assumptions of each data source and performed a few adjustments to build a consistent approach. The table below outlines the different assumptions underlying the construction of variables in the power sector according to various data sources and correction is CPAT. Green cells indicates that no adjustments have been made, whereas orange cells provide adjustments made in CPAT. As the study of Bogdanov et al. (2019) is based on the data sources listed in the table, it is not incorporated in the table.

As the various data sources rely on disparate assumptions under a few aspects, adjustments are made to build a consistent database to be fed into CPAT. As such, the following adjustments are performed.

Costs in time: The latest version of CPAT relies on data in 2019. As costs in time may vary depending on status of the power plant (e.g. operational, under construction, authorized, etc.), the retained approach first aims at building time series based on the available data points in time across the different data sources. Longest time series span from 1983 to 2040. While all sources focus on operational power plants or in the pipeline for commissioning after 2019, Enerdata considers a multitude of statuses, including cancelled or announced projects. Therefore, we filter the status of the plants and select only plants that are operational until 2020. From 2021 to 2040, only announced and authorized projects, power plants under construction and PPA signed are considered in the construction of time series. In the case of Bogdanov et al. (2019), which provide data every five years (i.e. starting from 2015), estimates for the year 2019 are approximated using the following weighting approach: $CAPEX_{2019} = 0.2 \times CAPEX_{2015} + 0.8 \times CAPEX_{2020}$.

Assumptions	IRENA	IEA&NEA	EIA	Enerdata	JRC	NREL
All variables						
First available year	The IRENA Renewable Cost Database provides data for installed power plant or in the pipeline for commissioning, mainly from 2010 to 2020. Data are retrieved for 2019.	The assumed commissioning date is 2025.	Data are provided for the first year that a new unit could become operational.	The tool provides data power generation assets on projects being announced, bidding process, operational, frozen, authorized, under construction, cancelled, stopped, mothballed, synchronized, suspended construction, FID, submitted, PPA signed.	Capital investment costs are from 2015 and forecast, based on learning curve model, costs trajectories under three scenarios for the years 2020, 2030, 2040 and 2050. In CPAT, retained costs are from 2020 and correspond to the "Diversified" scenario.	The database is US-focused and provides forecast estimations from 2019 to 2050.
Capital cost/Fixed and variable operations and maintenance costs						
Capital costs are overnight	Total installed project cost includes fixed financing costs. In CPAT, the data are refined to subtract financing cost.	The overnight cost includes preconstruction (owner's), construction (engineering, procurement, and construction) and contingency costs, but not interest during construction (IDC).	Overnight costs exclude interest accrued during plant construction and development. Overnight capital cost includes contingency factors and excludes regional multipliers (except as noted for wind and solar PV) and learning effects.	The tool enables users to have an overview of the overnight costs by energy, technology, zone, country for power generation assets currently operating or projects under development.	The authors confirm that costs do not include IDC, therefore it can be assumed that all costs are before the start of the construction.	Capital costs are overnight.
Costs are real in US dollars	All costs presented are denominated in real, 2019 US dollars (i.e. after inflation has been considered).	All cost figures are in USD 2018 and all variables are real, i.e. net of inflation.	Total Construction Costs should be provided in nominal dollars by power plants. ¹² A net present value –accounting for the inflation rate– capital budgeting methodology to evaluate investment options for new power plants is then employed.	All costs presented are denominated in real, 2019 US dollars.	The authors confirm that all monetary units are reported in euro for the year 2015 (real).	Capital costs are in real, 2019 US dollars.
Thermal efficiency						
In net calorific value	Efficiency is not reported.	Electrical conversion efficiency is mentioned in the report, but net or gross is not specified. Based on subsequent chapters, LHV is mentioned.	The instruction document defined the heat rate as the amount of fuel, measured in BTU necessary to generate one net kilowatt-hour of electric energy.	Efficiency is not reported.	Efficiency is not reported.	The authors use a heat rate. To express the efficiency of a generator or power plant as a percentage, the heat rate is converted in net calorific value.

Figure 3.35: Assumption underlying the construction of power data

Overnight costs: Capital costs are in principle excluding interest payments during construction time. However, IRENA Renewable Cost database provides total installed costs, namely including overnight costs. To adjust data from overnight costs, two information are needed:

- The construction time (n_{cons}) data for each renewable technology. This information is derived from both EIA and IEA&NEA. The average of the two sources of information is used as in the table below.
- The weighted average cost of capital ($wacc$). Following Steffen (2020), the WACC is roughly 7.5% for OECD countries and 10% for non-OECD countries. We thus apply the following rates:

Income Level	WACC Assumed
HIC	7.5%
UMIC	10.0%
LMIC	12.5%
LIC	15.0%

- Finally, the following formula is used to subtract overnight costs: $\frac{\text{CapEx}_{\text{IRENA}}}{(1+wacc)_{\text{cons}}}$.

Technology	Average time (year) for construction
Biomass	4.0
Solar (Utility-scale PV)	1.5
Geothermal power	4.5
Hydropower	4.5
On-shore wind	2.0

Costs are in USD and real (i.e. net of inflation): Only BNEF database displays nominal data. Monetary data are thus adjusted based on the US GDP deflator indicator. In the case of JRC and Breyer, data are real but denominated in EUR. The 2019 average EUR/US exchange rate is applied.

Efficiency in Net Calorific Value: The differences between net and gross calorific values are typically about 5% to 6% of the gross value for solid and liquid fuels, and about 10% for natural gas. Therefore, based on the original (GCV) data from BNEF, we approximate the NCV by applying a 10% increase for natural gas and 5.5% for the other technologies considered on the GCV values.

Lifetime assumptions: Lifetime information is given for all types of technologies considered in CPAT except for biomass. A lifetime of 35 years for power plants specialized in biomass is supposed.

3.4.4.4 Estimation of the power sector characteristics

To estimate power sector characteristics in 2019, simple averages of available data points are computed. In the first stage, in order not to overweight one data source over another, the averages are calculated by data source, as a data source may provide different data at a given time and for the same technology because data are project-based. In a second step, the calculation of averages is deployed in the following order of priority: by country, by CPAT region²², and globally. More specifically, to construct a dataset for the year 2019:

- CapEx is estimated based on 2019 data points only; 2019 is retained as a commissioning year for power plants.
- For Fixed and Variable OpEx, Efficiency and Capacity Factor, due to data limitation, closest trends are included (i.e. the average includes estimates for plants commissioning between 2015 and 2025). This approach is reasonable because these variables do not vary greatly from year to year.

²²CPAT regions are East Asia & Pacific (EAS), Europe and Central Asia (ECS), Latin America (LNC), Middle East North Africa (MENA), North America (NAC), South Asia (SAS), Sub-Saharan Africa (SSF). Due to their specific nature, China, Korea and Japan are treated separately from the rest of the Rest of Asian regions and not included in regional averages.

Forecasting CAPEX:

From 2020 to 2022

Evidence over the recent years shows a surge in international metals and minerals prices. As renewable technologies are more metals and minerals than non-renewables (Boer, Pescatori, and Stuermer (2021)²³), rising metals/minerals costs can be expected to increase the relative cost of new renewables investment. Projected capital expenditure costs for investment in new renewable and non-renewable capacity were therefore upscaled. Metals and all other commodities are expected to increase by about 2 times in 2022-3²⁴ compared to 2020 levels and assuming that these primary inputs into renewables account for roughly one tenth of the total of renewables up-front investment costs, which are themselves about 75% of total costs for renewables (Hirth and Steckel (2016)), the increase of CapEx for renewables would be about 15% in 2022-3 compared to 2020. However, as a part of this increase might be captured in 2020-1 historical data, the CapEx increase in new renewable and non-renewable capacity was upscaled by 10% and 5% in 2022 respectively.

From 2023 onwards

Among renewable energies, solar and wind are subject to the highest learning rate. Consequently, the learning rate approach is applied to these two technologies, while others, i.e. coal, oil, natural gas, and nuclear, and other renewables, are not subject to a learning rate nor to different scenarios and are assumed to be constant over time, i.e. after 2023.

The learning rate method is commonly employed to estimate development of costs over time and holds the advantage of being relatively easy to measure. With specific learning rate to technologies, this approach indicates the price reduction of the considered technology (i.e. the performance indicator) arising from every doubling of cumulative installed capacity (experience rate). Experience does not cause costs to drop directly. While it is believed to be correlated to changes in the production process (e.g. R&D, technical innovation, economies of scale or labor productivity) or the product itself (e.g. design), the model does not identify the factor of cost reduction. More sophisticated models include component-based learning costs, multi-factor learning curves (Rubin et al. (2015)) or an approach based on probabilistic cost forecasting methods (Way et al. (2022)).

Cost reduction in time, accounting for the performance and experience indicators, is expressed by:

$$Cost_t = Cost_0 \left(\frac{Cap_t}{Cap_0} \right)^{(-\varepsilon)}$$

where $Cost_t$ is the unit cost of the considered technology in year t after the deployment of cumulative installed capacity of Cap_t unit. Similarly, $Cost_0$ stands for CapEx in year 0 at

²³For the IMF's Energy Transition Metals Index see <https://www.imf.org/en/Research/commodity-prices>

²⁴<https://www.imf.org/-/media/Files/Publications/WP/2021/English/wpia2021243-print-pdf.ashx> or <https://www.imf.org/-/media/Files/Research/CommodityPrices/WEOSpecialFeature/october-2021-commodity-special-feature.ashx>

cumulative deployment capacity of Cap_0 unit. ε denotes the experience parameter. The learning rate (LR) is thus:

$$LR = 1 - 2^\varepsilon$$

where the parameter 2^ε is known as the learning rate ratio or progress ratio and reflects the slope of the learning curve.

The underlying idea is to highlight the cross-country transferability of a country's learning effects. For wind and solar only, we use capacity projections from the IEA Stated Policy (STEPS)²⁵ and Net Zero (NZE)²⁶ scenarios, then experience Parameters extracted from Way et al. (2022).

We consider four different scenarios²⁷:

- The **low scenario**: we use the IEA STEPS scenario for capacity projections data, and a low learning rate parameter (equal to mean – standard deviation ; 0.276 for Solar, 0.153 for Wind)
- The **medium scenario**: we use the IEA STEPS scenario for capacity projections data, and a medium learning rate parameter (0.319 for Solar, 0.194 for Wind)
- The **high scenario**: we use the IEA NZE scenario for capacity projections data, and a medium learning rate parameter (0.319 for Solar, 0.194 for Wind)
- The **very high scenario**: we use the IEA NZE scenario for capacity projections data, and a high learning rate parameter (equal to mean + standard deviation ; 0.362 for Solar, 0.235 for Wind)

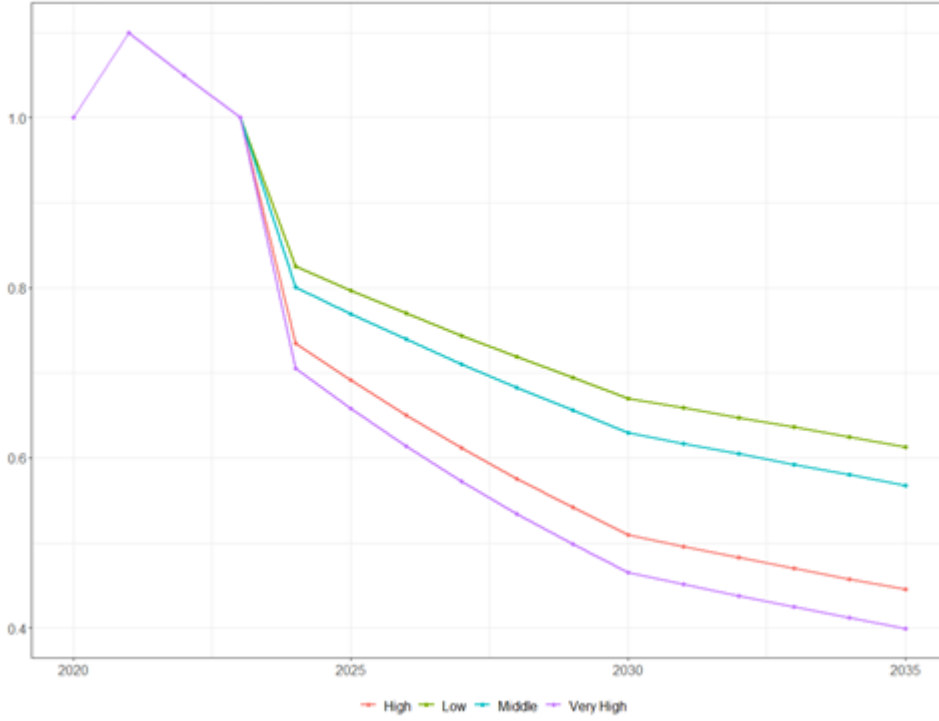
Below are the capital expenditures projections for the case of solar energy, for all the four scenarios.

²⁵IEA Stated Policies Scenario (STEPS)

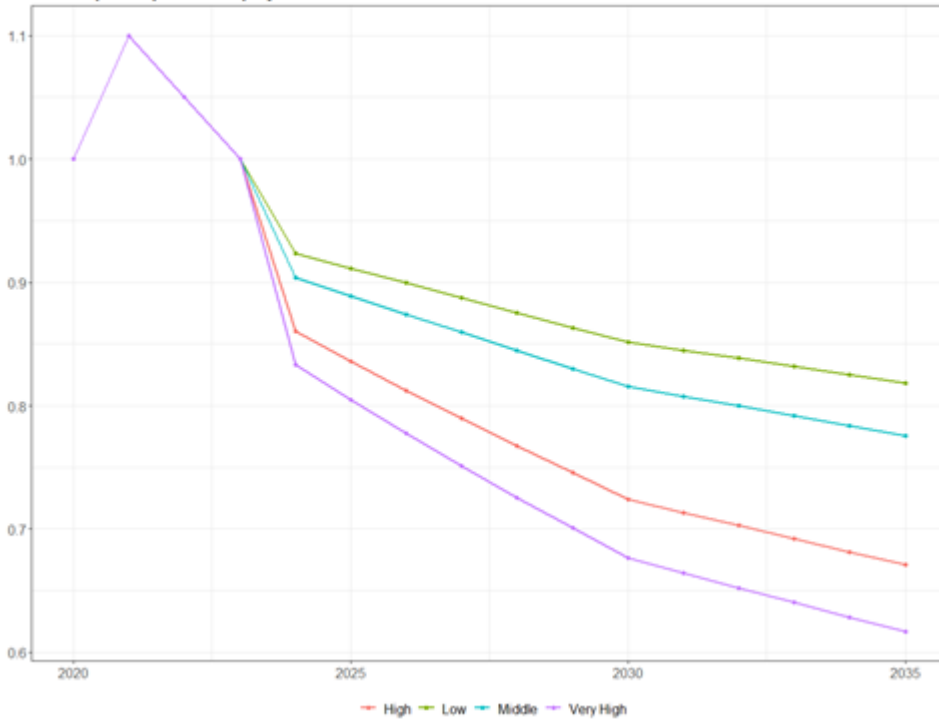
²⁶IEA Net Zero Emissions by 2050 Scenario (NZE)

²⁷All experience parameters are extracted/calculated from [Rupert Way, Matthew C. Ives, Penny Mealy, J. Doyne Farmer, 2022](#)

Solar capital expenditures projections



Wind capital expenditures projections



Storage costs: Utility-scale battery storage systems differ slightly from other technologies as they store produced electricity by generators or pulled from the electric grid. These systems then redistribute the power based on the demands. It is worth noting that battery storage costs are commonly expressed in kWh, although one fraction of these costs, the power costs, are measured in kW. We follow Cole, Frazier, and Augustine (2021) and express the costs of battery as follows: $\text{TotalCost} \left(\frac{\text{USD}}{\text{kWh}} \right) = \text{EnergyCost} \left(\frac{\text{USD}}{\text{kWh}} \right) + \text{PowerCost} \left(\frac{\text{USD}}{\text{kW}} \right) / (\text{Duration} (\text{hr}))$

Several types of battery exist, typically varying from 1h to 4h storage battery. In CPAT, costs for battery correspond to 2h storage battery. Forecast storage costs are based on the work of Cole, Frazier, and Augustine (2021) and Augustine and Blair (2021)²⁸. The authors base their estimations on current literature and data for Li-Ion Battery Storage, 60 MW, 240 MWh storage (4 hours) in the United-States are used as representative data. Costs for 2h storage battery are then estimated based on the above formula and expressed in kW²⁹. In particular, all values are given in 2019 U.S. dollars, using the Consumer Price Index (BLS, 2020) for dollar year conversions. Projections use an inflation assumption of 2.5% per year. In the same vein as for wind and solar, three scenarios are developed. The low, middle and high scenarios correspond to the minimum, median and maximum points, respectively. Augustine and Blair (2021) follows the approach in Cole, Frazier, and Augustine (2021), where data points between 2020, 2025, 2030 and 2050 are derived from a linear interpolation.

Decommissioning costs: Decommissioning takes place after a power plant retires. Notably, retirement and decommissioning are different. Retirement indicates that the plant is no longer producing electricity, but assets such as buildings, turbines, boilers or other equipment are left on site. The decommissioning process refers to dismantlement, environmental remediation and restoration of the site. While much of the literature focuses on decommissioning costs for nuclear power plants, data on decommissioning costs for other types of technology are scant. The following data sources are used in CPAT:

- Raimi (2017) provides estimates on decommissioning costs per type of technologies (off-shore and onshore wind, coal, concentrated solar, solar PV and petroleum and gas) based on a survey of the literature. Data are expressed at 2016 U.S. dollar prices;
- Neri et al. (2016) presents data on nuclear power plant decommissioning costs based on surveys answered by nuclear power plants located in Europe. Data are expressed at 2013 U.S. dollar prices;
- Duke Energy Corporation³⁰ is a nuclear power plant that submitted information to the US authority on the cost of decommissioning. Data are expressed at 2017 U.S. dollar prices; and
- Water Power & Dam construction³¹ estimates, based on information on dam destruction in the United-States, that decommissioning costs can be 20-40% of new construction

²⁸Data are available at: <https://data.openei.org/submissions/4129>

²⁹To measure data in kWh, costs are divided by the ratio kW/kWh (i.e. 2h).

³⁰The estimate is taken from the following article, based on Duke Energy: <https://www.powermag.com/data-shows-nuclear-plant-decommissioning-costs-falling/>

³¹See <https://www.waterpowermagazine.com/features/featuredecommissioning-dams-costs-and-trends/>

costs.

In CPAT, decommissioning costs are expressed as a percentage of global upfront costs. To this purpose, for nuclear, estimates retrieved from these studies are averaged. The ratio of the available data for decommissioning costs to the global CapEx (US/MW) data by technology type, are then used to express decommissioning costs as a percentage of CapEx. For natural gas, the average between estimated decommissioning costs for petroleum and gas (various types) is used as decommissioning costs. For hydropower, based on the above-mentioned study, it is assumed that decommissioning costs amount to 20% of CapEx.

3.4.4.5 References

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3.5 Emissions

This section describes how GHG emissions estimation and emissions are accounted for in CPAT and how they are projected in each sector.

3.5.1 Overview

In CPAT, emissions are projected in two ways: i) energy-related emissions are based on a model, that is estimations of energy consumption (see Section 3.3) in the different sectors are converted into GHG emissions by the means of an emission factor; and ii) non-energy related emissions are forecasted based on particular assumptions. Greenhouse gases (GHGs) emissions are presented following the UNFCCC Inventory category, and scaled to the inventory’s base year. The table below summarizes the approach taken to forecast emissions forward.

For energy related emissions:

Pollutant	Assumptions to forecast emissions
Carbon dioxide (CO_2)	Corresponding emissions are calculated by multiplying energy consumption by emissions factors. The model starts from observed value for emissions.
Methane (CH_4)	We multiply a calibration factor (equal to the ratio of the 2019 energy-related methane emissions and the 2019 Global Warming Potential (GWP100) for methane emissions) by the GWP100 for methane emissions of the associated year.
Nitrous oxide (N_2O)	Total energy-related nitrous oxide emissions are scaled to carbon dioxide emissions.

Fluorinated F-gases emissions are historically equal to zero and are thus assumed to be equal to zero in the future.
(F-gases)

For non-energy related emissions:

Emission type	Pollutant	Assumptions to forecast emissions (<i>in the case of forecasts based on a growth effect, GDP or population, we use specific sectorial elasticities</i>)
Industrial emissions	CO_2 , CH_4 , N_2O , F-gases	The growth rate is based on changes in energy-related industrial CO_2 emissions.
Agriculture emissions	CO_2 , N_2O , F-gases	Non-energy agriculture emissions are forecasted based on the GDP and population growths (and a proxy for additional mitigation efforts – if selected by the user). There is however a specific treatment for CH_4 agricultural emissions.
Agriculture emissions	CH_4	CH_4 agricultural emissions are calculated by multiplying the agricultural production with the after abatement methane emission factor. Agricultural production is obtained by accounting for the GDP and population growth's effect on the previous year's production, and the associated change in oil producer prices caused by the methane fee. We then multiply this emission value with the Global Warming Potential of methane for non-fossil fuel emissions of the associated year.
Land Use, Land-use Change and Forestry (LULUCF)	CO_2 , N_2O	Forecasted non-energy CO_2 and N_2O emissions for LULUCF are driven by a sink activity growth and the ratio of the growth in emissions for the carbon tax scenario to the increase in emissions for the baseline scenario (also called 'additional mitigation effort'). However in the case of N_2O emissions, we also take into account the population growth effect.
Land Use, Land-use Change and Forestry (LULUCF)	CH_4 , F-gases	Forecasted non-energy CH_4 and F-gases emissions for LULUCF are driven the growth in emissions for the carbon tax scenario to the increase in emissions for the baseline scenario (also called 'additional mitigation effort'). However in the case of F-gases emissions, we also take into account the population growth effect.

Emission type	Pollutant	Assumptions to forecast emissions (<i>in the case of forecasts based on a growth effect, GDP or population, we use specific sectorial elasticities</i>)
Waste and Other	CO_2 , N_2O , F-gases, CH_4 for Other only	For waste and other emissions, forecasted estimates are determined by the population growth effect and the additional mitigation effort. Those factors multiply the previous year's emissions value.
Waste	CH_4	CH_4 waste emissions are calculated by multiplying the waste production with the after abatement methane emission factor. Waste production is obtained by accounting for the GDP and population growth's effect on the previous year's production, and the associated change in oil producer prices caused by the methane fee. We then multiply this emission value with the Global Warming Potential of methane for non-fossil fuel emissions of the associated year.

Emissions have **two dimensions**:

- **Pollutants:** Carbon dioxide (CO_2), Methane (CH_4), Nitrous oxide (N_2O) and Fluorinated gases (F-gases). GHG emissions include those in the UNFCCC inventories (CO_2 , CH_4 , N_2O and Fluorinated Gases (or F-gases), including PFCs, HFCs SF6, and NF3). Note that the mitigation also presents short-lived air pollutants (PM2.5, NOx, SO2, CO2, NMVOC, BC, OC, CH4 and CO); the methodology for these is covered in the air pollution module documentation.
- **Sectors:** Energy-related sectors (i.e., Transport, Power, Industry, Building, and Other energy use), as well as non-energy-related sectors (i.e., Agriculture, Industrial Process, LULUCF, Waste and Other). It is important to note that some parts of the sectors accounted for in the non-energy sectors are also reflected in energy-related sectors. For instance, Agriculture also appears under the 'Building' sector, under 'Food and Forestry' sub-sector (for more information, see Appendix B).

CPAT considers territorial rather than consumption-based emissions. This means that, for example, if some natural gas is imported but subject to leaks upstream in extraction before it arrives at the country concerned, these methane emissions are not counted in the emissions of a natural gas power station. However, an extracting country will include those leaks. Similarly, the emissions from imported goods are not included, whereas those associated with exported goods are included.

In what follows, we first define the role of emission factors and their sources. Second, we present the approach adopted for energy-related emissions by fuel and sector. Third, we describe the estimation of non-energy-related emissions in non-energy sectors. We use the index p to refer to the type of GHG (CO_2 , CH_4 , N_2O and F-gases). The variable em_{occup}

denotes the estimation of emissions under scenario o , country c , UNFCCC sector u , and for pollutant p and at year t . Total GHG emissions are the sum of both energy and non-energy related emissions: $em_{oc,GHG,t} = em_{ocER,GHG,t} + em_{ocNER,GHG,t}$. Finally, the section explains how NDCs are accounted for in CPAT.

3.5.2 Notation

The table below presents the notations used in the section and the name of the variables to which they correspond. Note that the units are reported as they were input into CPAT, but further conversions are made to ensure that they match our calculations.

Notation	Variable	Unit
em	Emissions	tCO ₂ /GJ
$\Delta em_{LUCF,t}$	LULUCF emissions decline	% per annual in absolute value of start year
ef	Emission factors	tCO ₂ /ktoe
F	Use of fuel	ktoe
fug	Methane fugitive and venting emissions	tCO ₂ /ktoe
gwp	Global warming potential from methane emissions	tCO ₂ /ktoe
red	Percentage of reduction of methane emission factor, due do abatement	%
mf	Methane fee	\$/tCH ₄
Y_{grow}	GDP growth	%
lp_{grow}	Population growth	%
ame	Additional (e.g. non-pricing) mitigation effort	%
ϵ_Y	Forward-looking real GDP-elasticity of fuel demand	%
ϵ_{lp}	Population elasticity	%

3.5.3 Emission factors

An emission factor is a coefficient that converts activity data into GHG emissions. It represents the average emission rate for a given fuel relative to consumption units. For instance, in the power sector, coal emits 3.931 ton of per ktoe.

The emission factors used are (as a default) fuel-, country- and sector-specific emissions from IIASA's GAINS model³². The user also has the option to use global emissions factors from

³²Note that IIASA Emission Factors include process emissions, but we scale them to UNFCCC inventory emissions to only cover energy-related emissions

the IEA.³³ The emission factors given by the IEA are scaled at a worldwide level, while those from IIASA are country specific. Also, IIASA emission factors include process and fugitive emissions in the distribution network from natural gas (which is why it is necessary to rescale them through the overall calibration to 2019 emissions). All emission factors are sector and fuel specific.

The user has the possibility in the dashboard to select the source of emission factors to be used. Global IEA emissions factors are also an option.

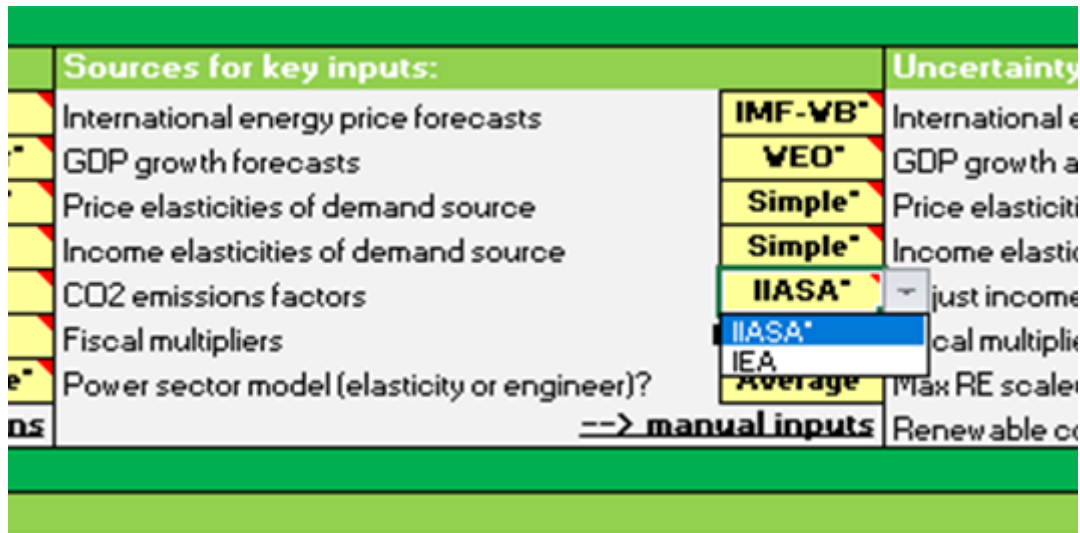


Figure 3.36: Selection of the source of emission factors

The emissions are given originally in $\frac{tCO_2}{GJ}$, then converted in $\frac{tCO_2}{ktoe}$ via a ktoe to GJ conversion factor of 41,868.

$$ef_{cgf, \frac{tCO_2}{ktoe}} = ef_{cgf, \frac{tCO_2}{GJ}} * 41,868$$

Furthermore, it is worth noting that we do not have data for emission factors for sector-fuel types when the energy consumption is close to zero. Therefore, the following rules are applied to define emission factors when missing:

Sector-Fuel types	Assumptions
Power sector-LPG	Equal to emission factors in the industrial sector
Road-LPG	Equal to emission factors in the building sector
Power sector-Kerosene and Road-Kerosene	Equal to emission factors in the building sector
Road-Coal	Equal to emission factors in the power sector
Road-Other oil products	Equal to emission factors for diesel

³³See <https://pure.iiasa.ac.at/id/eprint/17552/>

Sector-Fuel types	Assumptions
All sectors-Biomass	Emission factors are equal to zero

3.5.4 Energy-related emissions

Energy-related emissions are estimated across sectors and by aggregating sectors (i.e., Transport, Power, Industry, Building, and Other energy uses) for the four GHGs (i.e. CO_2 , CH_4 , N_2O and F-gases). In this section, the index $u = E$, denotes the energy-related sectors.

3.5.4.1 Carbon dioxide (CO_2)

Energy-related CO_2 emissions are calculated by multiplying energy consumption by emissions factors. Emissions are multiplied by 10^{-6} as the emission factor ef is given in $tCO_2e/ktoe$ and the fossil fuel consumption F is given in $ktoe$, to obtain emissions in $mtCO_2e$. We neglect this unit transformation in the description below.

In 2019, these CO_2 energy-related emissions are scaled to UNFCCC inventory emissions such that base-year emissions are equal in the model and the inventory. After 2019, these emissions are thus calculated, for each fuel f and for a year t , as the multiplication of the fossil fuel's consumption for year t by the sector's associated to emission factor:

$$em_{ocEsft} = F_{ocEsft} * ef_{cEsfp}$$

where o represents scenario, s , sector, f , fuel type, p , GHG (e.g., CO_2) and t the year.

CO_2 emissions are determined across all fuels and across all sectors (and grouping sectors). Total energy emissions are determined as the sum across sectors and fuels (for energy related emissions $u=E$)

$$em_{ocpt} = \sum_s \sum_f em_{ocsfpt}$$

CPAT also covers the other parts of the UNFCCC inventories (i.e., GHGs other than CO_2 , and other categories than energy-related GHGs). Methane emissions have a specific treatment for the most part. In the case of energy-related emissions, we treat methane emissions intensities for fossil-fuel production. They are inputted to the UNFCCC inventories emissions calculations. This is detailed in the next section.

3.5.4.2 Methane (CH_4)

Energy-related methane emissions calculations are based on the same logic as for CO_2 emissions, except for fossil fuel production emissions. Therefore we will only focus here on fossil fuel production. Oil and natural gas are first grouped together, then we consider downstream fossil fuel and biomass. We finally multiply the fossil fuel production with the associated emission factor, per year. This gives us the energy-related methane emissions.

- **Methane emission intensities for fossil-fuel production**

The initial step involves the calculation of emissions intensity by determining baseline emission factors for each unit of energy produced or extracted. In the policy scenario, these emission factors undergo modification based on the application of a methane fee. Abatement cost curves specific to methane are utilized, employing a functional form represented by a power function structure where a coefficient A is multiplied by the methane fee, subsequently raised to the power of coefficient B. This approach results in a reduction of the emission factors by a certain percentage relative to the baseline level.

The emissions are calculated through:

$$em_{oc,oil/nga/coa,CH_4,t} = prod_{oc,oil/nga/coa,t} * ef_{c,oil/nga/coa,CH_4,AfterAbatement,t}$$

with $prod_{oc,oil/nga/coa,t}$ being the production of crude oil or natural gas or coal at time t , in ktoe.

- **Change in fossil-fuel production/demand**

We use the assumptions on the global demand for oil, natural gas and coal that come from the IEA, and we then assume that the country level change and production just follows the global trend. If there's some path pass through, then the global trend is adjusted downwards for reduced demand.

Focusing more on that production calculation, we take the percentage change of producer prices for oil/natural gas/coal due to the methane fee (if defined by the user) at time t , then the ratio of the global demand of oil/natural gas/coal at time t by the same demand a $t - 1$ (we take an average between oil and gas, and treat coal separately), and we finally multiply all of those factors by the production value at $t - 1$. If there is a pass-through of carbon price/methane fee to the consumers, this is also taken into account.

The methane emission factor After Abatement for a specific fuel is equal to the methane emission factor for that fuel on which we apply a percentage of reduction.

Specifically, this percentage of reduction red is obtained based on the value of the methane fee mf , and a power function structure such as:

$$red_{ocf,CH_4,t} = A * m f_t^B$$

where A and B are the inputs for the abatement curve.

Regarding the oil and gas sector, an assumption is made that a portion of methane emissions is mitigated through flaring, which facilitates the conversion of methane to CO₂. The calibration of this reduction quantity is based on an EPA dataset.

3.5.4.3 Nitrous oxide (N₂O) and Flourinated gases (F-gases)

N₂O and F-gases energy-related emissions estimates follow the below rules:

- **Total energy-related N₂O emissions** are scaled to CO₂ emissions. For $t > 2019$:

$$em_{oc,N_2O,t} = em_{oc,N_2O,(t-1)} * \frac{em_{oc,CO_2,t}}{em_{oc,CO_2,(t-1)}}$$

- **Total energy-related F-gases emissions** ($p = PFC_s, HFC_s, SF6, NF3$) are historically zero for the energy category. For $t > 2018$: $em_{ocpt} = 0$.

3.5.5 Non-energy related emissions

Non-energy-related emissions are estimated across non-energy-related sectors (i.e. Agriculture, Industrial Process, LULUCF, Waste, and Other) for the four GHGs (i.e. CO₂, CH₄, N₂O and F-gases). Non-energy-related emissions in the different sectors considered above are determined based on various sector-specific assumptions. In particular:

- In the **industrial processes and product use** sector, the growth rate is based on changes in energy-related industrial CO₂ emissions.
- Non-energy **agriculture** emissions are forecasted based on the GDP and population growths.
- Forecasted non-energy emissions for **LULUCF** are driven by a sink activity growth and the ratio of the growth in emissions for the carbon tax scenario to the increase in emissions for the baseline scenario. Net sources and net sinks are treated differently (see below)
- For **waste and other** emissions, forecasted estimates are determined by population growth.

3.5.5.1 Industrial processes and product use

In the industrial processes and product use sector, the growth rate is based on changes in energy-related industrial CO_2 emissions.

In what follows, the index $u = I$, standing for Industrial Processes and Product Use.

Non-energy-related industrial CO_2 emissions are forecasted based on an industrial energy-related CO_2 emissions rate ($\Delta em_{ocP,CO_2,t+1}$). Therefore:

$$\Delta em_{ocI,CO_2,t+1} = \begin{cases} \max\left(0, \frac{em_{ocEind,CO_2,t+1}}{em_{ocEind,CO_2,t}} - 1\right) & \text{for } t = 2019 \\ \frac{em_{ocEind,CO_2,t+1}}{em_{ocEind,CO_2,t}} - 1 & \text{for } t > 2019 \end{cases}$$

The index Eind stands for the energy-related emissions in the industrial sector.

Importantly, it is assumed that other pollutants p are scaled on the same industrial CO_2 emissions rate. In other words, emissions of each pollutant for a year t is the sum of emissions from the previous year $t - 1$ adjusted by the change in industrial CO_2 emissions Δem .

For $t > 2019$: $em_{ocIp,t} = em_{ocIp,t-1} * (1 + \Delta em_{ocI,CO_2,t})$

3.5.5.2 Agriculture

Non-energy agriculture emissions (except for methane emissions) are forecasted based on the GDP and population growths (and a proxy for additional mitigation efforts – if selected by the user). We consider livestock and rice production.

For this section, $u = A$.

Agricultural emissions are projected using a similar approach to the rest of CPAT: a reduced-form approach with elasticities, notably per capita income ϵ_Y (GDP growth: Y_{grow}) and population ϵ_{ip} specific to each UNFCCC emissions sector (population growth: lp_{grow}).

In addition, the user has the option to assume that non- CO_2 GHGs scale with fossil CO_2 , which is a proxy for additional (e.g., non-pricing) mitigation effort (*ame*) in the UNFCCC categories. **This option, in effect, turns a carbon price into an all-sector (incl non-energy sectors) GHG tax (incl. methane, N20 etc).**

For each pollutant (except methane) and for $t > 2019$:

$$em_{ocAp,t} = \frac{em_{ocAp,t-1}}{ame_{A,t-1}} (1 + Y_{\text{growth}})^{\epsilon_Y} * (1 + lp_{\text{grow}})^{\epsilon_{ip}} * ame_{At}$$

In the case of non-energy agriculture methane emissions, we can have a change in the agriculture and waste production if there is a pass-through of the methane fee. Unlike the oil/natural

gas/coal production function explained in the energy-related methane emissions section, the production function for agriculture takes into account the effect of population and GDP growth. We also consider the percentage change of oil producer prices caused by the methane fee. Then, the agricultural sector has its own inputs for the abatement curve in order to obtain the associated emission factor.

3.5.5.3 Land use, land-use change and forestry

LULUCF GHG are assumed to be flat in the baseline and policy scenario for net sink countries (where sinks of GHGs exceed sources). For countries where LULUCF is a source, we assume an exogenous decline of 2.5% per annum in both the baseline and policy scenario. The user should note that this rate can be adjusted in the dashboard.

Mitigation module (macro & energy effects)	
<-- Advanced mitigation options	
General assumptions	
First year of model calculations?	2019
Nominal results in real terms of which year?	2021
Use energy balances or (CPAT) energy consumption	Consumption
Generate Matrix of Energy Consumption Projections	2019
NDC submission	Latest*
Use 'world' (USA) or country-specific discount factor	World
Sum all oil products in industrial transformation sector	Converted
Adjust Annex I country energy-related CO2 EFs to r	Yes*
Adjust non-Annex I country energy-related CO2 EF	Yes*
<i>Info: adjustment to EFs</i>	1.40
Industrial process emissions scale with industrial CO	Yes*
LULUCF emissions decline at % pa (in absolute value)	2.5%
Global energy demand scenario	Stated Policies*

Figure 3.37: LULUCF emissions decline rate

At the global level, this aligns with approximately the midpoint of IAMs' projection for LULUCF. Where the country assumes 'additional mitigation effort in non-energy sectors' LULUCF GHGs decline at the rate of energy .

For this section, $u = L$.

It is considered that a defined amount of emissions can be subtracted yearly, based on the 2019 level. Therefore, we introduce the LULUCF emissions decline $\Delta em_{L,t}$ (in annual %, in absolute value of the start year).

- For $p = CO_2$:

In the case of CO_2 , we create a condition to model the sink activity of LULUCF ($em_{ocLpt} < 0$ or > 0). In both cases, we subtract an annual capture of CO_2 based on the LULUCF emissions decline $\Delta em_{L,t}$. If the emissions of the previous year $t - 1$ are positive, we scale the emissions with the ratio $\frac{ame_{cLp,t}}{ame_{cLp,t-1}}$ with $ame_{cLp,t} = \frac{em_{P,cLt}}{em_{B,cLt}}$, which represents the ratio between energy-related emissions under a policy and baseline scenario.

For $t > 2019$:

$$em_{ocLpt} = \begin{cases} em_{ocLp,t-1} - \|em_{ocLp,2019} \cdot \Delta em_{L,t}\| & \text{if } em_{ocLp,t-1} < 0 \\ \frac{em_{ocLp,t-1}}{ame_{cLp,t-1}} \cdot ame_{cLp,t} - \|em_{ocL,2019} \cdot \Delta em_{L,t}\| & \text{if } em_{ocLp,t-1} \geq 0 \end{cases}$$

- For $p = CH_4$:

The same logic as for CO_2 is used, without considering the condition for sinks.

For $t > 2019$:

$$em_{ocLpt} = \frac{em_{ocLp(t-1)}}{ame_{B,L,t-1}} * ame_{P,Lt} - |em_{ocLp,2019} * \Delta em_{L,t}|$$

- For $p = N_2O$:

In the case of N_2O , we assume the level of emissions to grow accordingly to the population growth lp_{grow} .

For $t > 2019$:

$$em_{ocLpt} = \frac{em_{ocLp,t-1}}{ame_{B,L,t-1}} * ame_{P,Lt} * (1 + lp_{grow}) - |em_{ocLp,2019} * \Delta em_{L,t}|$$

- For F-gases ($p = PFC_s, HFC_s, SF6, NF3$):

In the case of F-gases, we assume the level of emissions to grow accordingly to the population growth lp_{grow} . However, it is the only case where we do not consider the LULUCF emissions decline.

For $t > 2019$:

$$em_{ocLpt} = \frac{em_{ocLp,t-1}}{ame_{B,Lp,t-1}} * ame_{P,Lt} * (1 + lp_{grow})$$

3.5.5.3.1 Waste and Others

For waste and other emissions, forecasted estimates are determined by population growth.

For this section, we consider that $u = W$ and O , denoting respectively Waste and Others type of emissions.

Waste emissions are projected using a similar approach to Agricultural emissions: a reduced-form approach with population growth elasticity ϵ_{lp} (population growth: lp_{grow}). We include again the additional (e.g. non-pricing) mitigation effort ame .

For each pollutant and for $t > 2019$:

$$em_{\text{ocupt}} = \frac{em_{\text{ocup},t-1}}{ame_{B,u,t-1}} * ame_{P,ut} * (1 + lp_{\text{grow},t})^{\epsilon_{lp}}$$

In the case of methane emissions, we can have a change in the agriculture and waste production if there is a pass-through of the methane fee.

3.5.6 National Determined Contributions

CPAT harmonizes National Determined Contributions (NDCs) for 192 countries to show target GHG emissions levels (excluding LULUCF) in 2030, based on several major NDC characteristics, that is conditionality and sectoral coverage. This section presents the different types of NDCs. Country cases illustrating how NDCs are calculated in CPAT are presented in Section 3.9.4 calculations.

3.5.6.1 Types of NDCs

There are different types of NDCs:

- **Business as usual (BAU) targets:** NDC target is a percent reduction from the country's BAU scenario. For example, Albania's NDC is 11.5% reduction in CO2 emissions compared to the baseline scenario in 2030.
- **Fixed targets:** NDC target is a fixed level of GHG/CO2 emissions in target (future) year. For example, Argentina's NDC is a cap of 359 MtCO2e net emissions in 2030.
- **Historical targets:** NDC target is a percent or fixed reduction from the level of emissions in past years. For example, Australia's NDC is 26 to 28% reduction below 2005 levels by 2030.
- **Intensity targets:** NDC target is a reduction in emissions intensity. For example, Uruguay's NDC is emissions intensity reduction (GHG/GDP) of 24% in CO2 from 1990 levels.

- **Unquantifiable targets:** NDCs with no specific emissions reduction commitments. For example, Saudi Arabia’s NDC: “The Kingdom will engage in actions and plans in pursuit of economic diversification that have co-benefits in the form of greenhouse gas (GHG) emission avoidances and adaptation to the impacts of climate change, as well as reducing the impacts of response measures.”

NDCs could also present conditional and unconditional targets:

- **Unconditional targets:** Countries would use their own resources and technologies to achieve unconditional goals.
- **Conditional targets:** Countries would need international support to achieve these (more ambitious) goals.

3.5.6.2 Harmonization of NDCs: Country cases

CPAT excludes LULUCF emissions from NDC calculations, so in case LULUCF emissions were included in initial document, the goals are recalculated with LULUCF, using the latest available data for LULUCF GHG emissions and user-identified growth parameters for these emissions. If not stated, we assume that the NDC target includes LULUCF.

By default, CPAT models the impact of carbon pricing on energy-related emissions. Hence, for countries with high levels of emissions from non-energy related sources (agriculture, waste, LULUCF), the calculations would imply a high burden on energy sector to achieve NDC goals. For more information, see Section 3.9.4 calculations, which presents examples of NDCs calculations.

3.6 Fiscal revenues

The fiscal revenues section in the mitigation tab of CPAT is organized as follows:

- Information about **total fuel expenditure**, broken down per fuels and sectors, and **revenues/losses from price controls** broken down per fuel. These data are not used in the calculation of fiscal revenues.
- **Policy coverage** showing the percentage coverage of CO2 emissions under the policy selected and for each sector group and fuel.
- **The different components of the fiscal revenues** detailed in the subsequent section.

3.6.1 Overview

Revenues from mitigation policies are estimated by comparing any revenues from the policy and fuel taxes, net of any outlays from fuel subsidies, in the baseline scenario with those in the policy scenario. Fiscal revenues in CPAT are calculated for several types of taxes, by fuel and sector. Revenue-raising policies include carbon taxes, ETSs with auctioned allowances, increases in fuel/electricity excises, and reductions in fossil fuel subsidies. Revenue-reducing policies include expenditures (e.g., on renewable subsidies) and regulations (which reduce the base of pre-existing fuel taxes).

CPAT differentiates two types of revenues:

- **Carbon tax revenues**, which are the result of the carbon tax multiplied by emissions factor and energy use.
- **Full revenues**, which include other taxes, VAT changes, excise duties, existing ETS schemes, etc. The changing revenues according to a carbon tax are not just simple revenues but also any changes associated with full revenues. For instance, there could be changes in subsidies due to changes in energy consumed.

A general formula for fiscal revenues calculations is:

$$rev_{ocfgt} = F_{ocfgt} * \varphi_{cgft} * ncp_{ocfgt}$$

where rev_{ocfgt} is the fiscal revenues in scenario o from country c from fuel f in sector g , F_{ocfgt} is the energy consumption, φ_{cgft} is the sector-fuel coverage and ncp_{ocfgt} denotes the tax (policy) rate per unit of energy consumption.

In the dashboard, the graph below (Figure 3.38) shows total additional (vs. baseline) fiscal revenues from the policy, net of renewable energy subsidies. Note that this includes base effects (for example, a reduction on the tax base due to the policy) on existing taxes and subsidies, so even a revenue-neutral policy that nevertheless changes the base of existing taxes will have some effects on these, net, revenues.

The user can also see total revenues (i.e. not against the baseline scenario) according to the different fuels, net of subsidies (Figure 3.39).

The remaining of the section presents the calculations of revenues and its breakdown in more details.

Notation	Variable	Unit
----------	----------	------

3.6.2 Notation

Notation	Variable	Unit
<i>rev</i>	Fiscal revenues	Real 2021 US\$bn
<i>F</i>	Energy consumption	ktoe
φ	Sector-fuel coverage	%
<i>ncp</i>	New Carbon Price	US\$/ton of CO ₂
<i>revExi</i>	Revenues from existing excises and other taxes	Real 2021 US\$bn
<i>cs</i>	Consumer-side subsidy	US\$/Gj
<i>fao</i>	Fixed/ad val part/other	US\$/Gj
<i>xct</i>	Current carbon tax	US\$/Gj
<i>xetsp</i>	Current ETS permit price	US\$/Gj
<i>revVAT</i>	Revenues from VAT	Real 2021 US\$bn
<i>vat</i>	Value added tax	US\$/Gj
<i>cstPs</i>	Losses from producer-side subsidies	Real 2021 US\$bn
<i>subDem</i>	Subsidized demand	Billion liters for oil, GJ for coal and natural gas and GWh for electricity
<i>pusF</i>	Per-unit fossil fuels subsidies	US\$/liters for oil, US\$/GJ for coal and natural gas and US\$/GWh for electricity
<i>cstRen</i>	Cost of renewable subsidies	Real 2021 US\$bn
<i>pusRen</i>	Per-unit renewable subsidies	US\$/kwh

3.6.3 Total revenues raised by policy

Fiscal revenues are calculated according to the selected power model (Elasticity, Engineer or Average) and are expressed in billions of dollars (in real terms based on the year 2021) and as a percent of GDP. Please note that revenues can be broken down per fuel. Total revenues are composed of:

- **Revenues from the baseline scenario** raised for each fuel and sector. The estimation of these revenues follows the general formula for fiscal revenues presented above (i.e., the carbon tax multiplied by emissions factor and energy use).
- **Revenues from existing excises and other taxes, including consumer-side subsidies.** This describes all existing taxes and consumer side subsidies. Excise and other taxes are composed of:

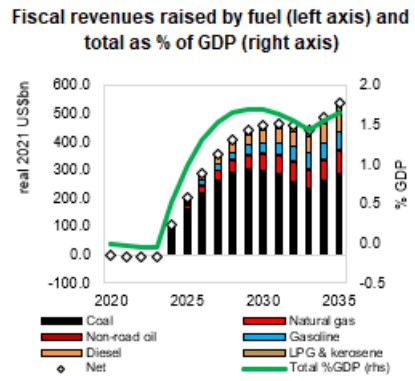


Figure 3.38: Dashboard: Fiscal revenues raised by fuel and total as % of GDP

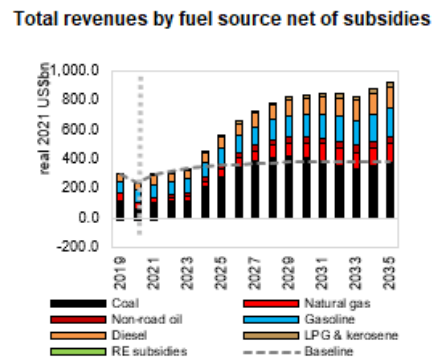


Figure 3.39: Dashboard: Total revenues by fuel source net of subsidies

- Consumer-side subsidy: cs_{ft} ;
- Fixed/ad val part/other: fao_{ft} ;
- Current carbon tax: xct_{ft} ; and
- Current ETS permit price: $xetsp_{ft}$.

For each fuel, we multiply the fuel consumption (minus the other energy use part, which is assumed not to be covered by excises) by the sum of all the current excises. If the existing ETS is EU ETS, then the excise and other taxes from current ETS permit price are not taken into account. It is worth noting that for coal and natural gas, the formula below is used across sectors as these fuels are broken down per data on excise taxes in the sector groupings (i.e., industry, buildings and power sectors).

Revenues from existing excises and other taxes, $revEx_{ft}$, are thus estimated as follows:

$$revExi_{ft} = \begin{cases} (F_{ocft} - F_{oc,oen,ft}) * (cs_{cft} + fao_{cft} + xct_{cft}) & \text{if } ExistingETS = EUETS \\ (F_{ocft} - F_{oc,oen,ft}) * (cs_{cft} + fao_{cft} + xct_{cft} + xetsp_{cft}) & \text{if } ExistingETS \neq EUETS \end{cases}$$

where F_{ft} denotes energy consumption and $F_{oen,ft}$ energy consumption in the Other Energy Use sector grouping.

For electricity, revenues from additional excise tax are also estimated based on the power prices determined in the engineer power model. The additional excise tax is multiplied by the energy use and the consumer-side tax/subsidy in the residential sector and the tax/subsidy on industrial users in the non-residential sector.

- **Revenues from additional excise tax** (if it exists – additional excise tax can be inputted in the Manual Inputs tab.) raised for each fuel and sector, calculating as the additional excise tax multiplied by the energy use. For electricity, however, it is worth noting that revenues from additional excise tax relies on the engineer power model estimations.
- **Revenues from VAT.** Following the same logic as for existing excises and other taxes and additional excise taxes, revenues from VAT are calculated across sector grouping as the multiplication of the fuel consumption (minus the other energy use part $F_{oen,f,t}$, which is assumed not to be covered by the VAT) by the associated VAT payment rate vat_{cft} :

$$revVAT_{ft} = (F_{ocft} - F_{oc,oen,ft}) * vat_{cft}$$

For electricity, revenues from VAT are obtained by multiplying the energy use by the VAT payment in the residential non-residential sectors.

- **Losses from producer-side subsidies.** Producer-side subsidies represent a loss and are thus subtracted from total fiscal revenues. They do not affect the calculation of prices in CPAT and thus revenues unless they are phased out, if they exist. Note that implicitly the underlined that we are using has already been adjusted for producer-side subsidies, in particular in the case of coal. Producer-side subsidies, $cstPs_{ocft}$, are defined as the product between the per-unit subsidies³⁴, $pusF_{ocft}$, and the subsidized demand, $subDem_{ocft}$:
- **Losses from producer-side subsidies.** Producer-side subsidies represent a loss and are thus subtracted from total fiscal revenues. They do not affect the calculation of prices in CPAT and thus revenues unless they are phased out, if they exist. Producer-side subsidies, $cstPs_{ocft}$, are defined as the product between the per-unit subsidies³⁵, $pusF_{ocft}$, and the subsidized demand, $subDem_{ocft}$:
- **Losses from producer-side subsidies.** Producer-side subsidies represent a loss and are thus subtracted from total fiscal revenues. They do not affect the calculation of prices in CPAT and thus revenues unless they are phased out, if they exist. Note that implicitly the underlined that we are using has already been adjusted for producer-side subsidies, in particular in the case of coal. Producer-side subsidies, $cstPs_{ocft}$, are defined as the product between the per-unit subsidies³⁶, $pusF_{ocft}$, and the subsidized demand, $subDem_{ocft}$:

$$cstPs_{ocft} = subDem_{ocft} * pusF_{ocft}$$

where subsidized demand is determined based on both global demand data from the IEA and domestic demand data directly estimated in CPAT. The estimation of subsidized demand differs depending on the fuel considered. For oil, subsidized demand is equal to global demand as it is a global traded product. Subsidized demand for coal and natural gas represent 50% of global demand and 50% of domestic demand. Finally for electricity, only domestic demand is used and depends on the power model selected. Subsidized demand can also vary according to the global energy demand scenario selected in the dashboard (see Figure 3.40). In addition, per unit subsidies are taken from the Prices section of CPAT. For coal, gasoline and natural gas, per unit subsidies correspond to the average across all sectors. Importantly, per unit subsidies are equal across sector grouping. For electricity, producer-side subsidies are retrieved from the non-residential sector (i.e., denoted as industrial sector) of the Power Prices section of CPAT, determined in the engineer power model.

³⁴For oil, it is worth noting that the component ‘other oil products’ is removed from the calculation as these types of fuels (e.g. light fuel oil) are not subsidized.

³⁵For oil, the component ‘other oil products’ is removed from the calculation as these types of fuels (e.g., light fuel oil) are not subsidized.

³⁶For oil, it is worth noting that the component ‘other oil products’ is removed from the calculation as these types of fuels (e.g. light fuel oil) are not subsidized.

Mitigation module (macro & energy effects)		
←-- Advanced mitigation options		
General assumptions		Adc
First year of model calculations?	2019	Pov
Nominal results in real terms of which year?	2021	Roa
Use energy balances or (CPAT) energy consumption data?	Consumption	Res
Generate Matrix of Energy Consumption Projections for NDC submission	2019	Indu
Use 'world' (USA) or country-specific discount factors?	Latest*	Fee
Sum all oil products in industrial transformation sector	World	Adj
Adjust Annex I country energy-related CO2 EFs to match 1.5C scenario	Converted	Enr
Adjust non-Annex I country energy-related CO2 EFs to match 1.5C scenario	Yes*	Veh
<i>Info: adjustment to EFs</i>	Yes*	Res
Industrial process emissions scale with industrial CO2 emissions	1.01	Indu
LULUCF emissions decline at % pa (in absolute value of 2019)	Yes*	Fee
Global energy demand scenario	3%	Res
Social cost of carbon (SCC) assumptions:	Stated Policies*	
Target-consistent carbon price by 2030 (for 'Target' option)	Stated Policies*	
NSCC discount rate (ρ)	Announced Pledge	
NSCC elasticity of marginal utility (μ)	Sustainable Development	
Global social cost of carbon (GSCC) source	Net Zero	
SCC (both NSCC and GSCC) - annual rise in real terms	2%	Fit
	1.5%*	Ove
	Target*	If ov
	4%	

Figure 3.40: Dashboard: Global energy demand scenario

- **Cost of renewable subsidies** (if applicable – renewable subsidies are defined by the user in the dashboard). If specified by the user, $cstRen_{ocft}$ represents the cost of implementing renewable electricity subsidy (or tax). In addition, the user can also add renewable subsidies under the baseline scenario. This cost is thus equal to the product between $pusRen_{ocft}$, the cost of renewable subsidies in \$/kWh (in real terms) and, g_{ocft} , the electricity supplied in the power sector according to the power model chosen.

$$cstRen_{ocft} = pusRen_{ocft} * g_{ocft}$$

These costs are estimated for each renewable energy, that is wind, solar, hydropower and other renewables.

3.6.4 Additional information

Revenue or losses from price controls and total fuel expenditures can also be found in the Fiscal Revenues section of CPAT. These estimations are not used in the calculation of the total fiscal revenues.

3.6.4.1 Revenues/losses from price controls

Revenues/losses from price controls, ctr_{ocft} , are calculated by multiplying fuel consumption across sectors (minus the other energy use part, on which price control does not apply) by the difference in fuel's international prices from the current year to the previous one, $pInt_{ocft} - pInt_{ocf,t-1}$, and by the portion of global energy price changes not passed-through into domestic prices, $pth_{ocft} - 1$.

$$ctr_{ocft} = (F_{ocft} - F_{oc,oen,ft}) * (pth_{ocft} - 1) * (pInt_{ocft} - pInt_{ocf,t-1})$$

3.6.4.2 Total fuel expenditures

Total fuel expenditures are not part of the fiscal revenues, but show the expenditures on fuel from a whole country perspective, as this is often relevant in developing countries wishing to minimize their import bill. Fuel expenditures are estimated for each fuel considered in CPAT and are expressed as the product between prices and energy consumption across all sectors.

3.7 Monetized social costs and benefits

In this section, the theoretical framework is first presented in order to explain the approach used to assess efficiency costs and domestic environmental co-benefits. Then, this section describes how energy externalities costs are estimated. Finally, these costs are used to calculate monetized welfare benefits.

3.7.1 Overview

Figure 3.41 provides a representation of the fossil fuel market, where supply and demand interact. Importantly, it is assumed that the energy demand responds to prices in the private sector, although the institutional setup could, in some markets, play a role in preventing prices from determining supply and demand.

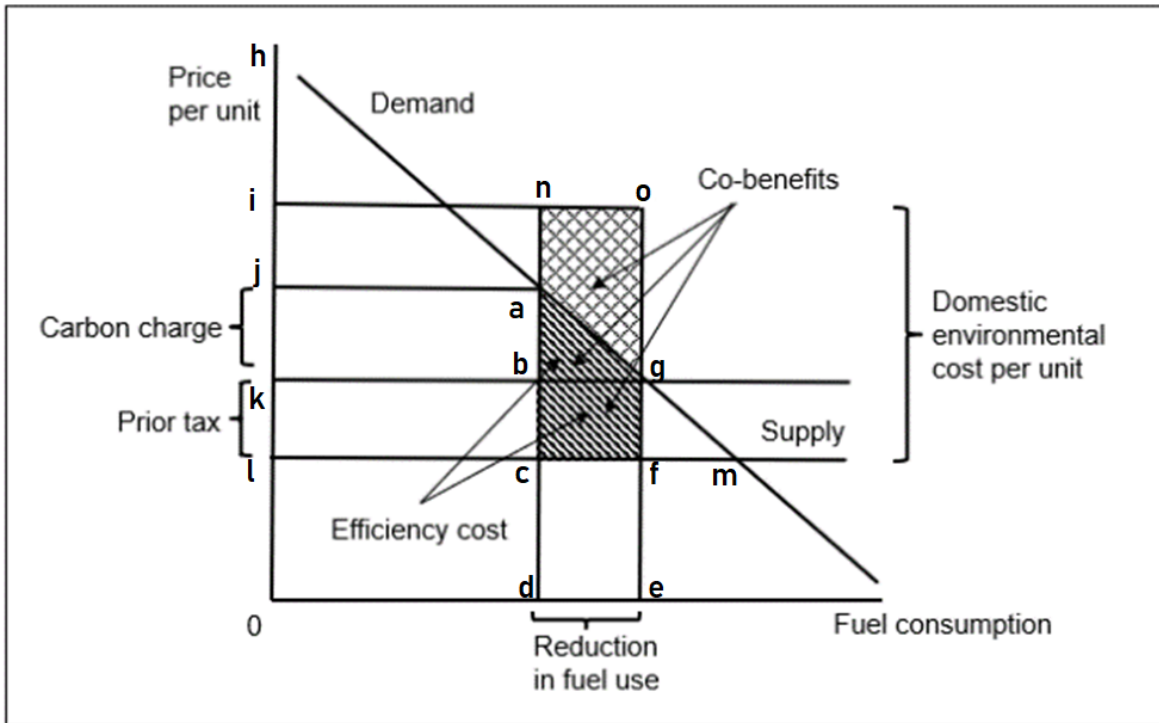


Figure 3.41: Efficiency costs and co-benefits in the presence of prior-tax and carbon charge

At any point, the height of the demand curve reflects the benefit to consumers from an extra unit of consumption, while the height of the supply curve (drawn as flat here because constant returns to scale is assumed) reflects the cost to firms of producing an extra unit. If there is no pre-existing tax or subsidy in the market, the consumer and producer price are equal, and

the market equilibrium is efficient (leaving aside environmental impacts) because the benefit to consumers from the last unit consumed equals the cost to firms of supplying that unit.

3.7.1.1 Efficiency costs without a prior tax

Introducing a carbon tax in a country is distortionary by nature from a local perspective (since it does not correct for a local externality per se), but with the aim of contributing to a global reduction in emissions (i.e., it contributes to reducing global externalities). Suppose a carbon charge, equal to a carbon tax times the fuel's CO₂ emissions factor, is now applied to the fuel. The charge drives a wedge between the price paid by fuel users and the price received by fuel producers and reduces fuel use, resulting in an economic efficiency cost indicated by the shaded triangle abg . This efficiency cost is equal to the loss of benefits to consumers from the fuel reduction, the integral under the demand curve or trapezoid $adeg$, less savings in production costs to firms, rectangle $bdeg$.

Alternatively, the efficiency cost can be interpreted as the loss in consumer and producer surplus ($jkga$) less revenue gains to the government where the latter is rectangle $jkba$. Consumer surplus reflects the benefits of fuel use to consumers less the amount they pay for the product ($jkga$) and is reduced from triangle hkg to triangle hja by the carbon charge. Producer surplus reflects revenue gains to firms less production costs consumption but is zero with and without the carbon charge as constant returns are assumed.

3.7.1.2 Efficiency cost in the presence of a prior tax

It is now supposed that a prior tax on fuel use is applied. This prior tax drives a wedge between the consumer and producer price in the initial equilibrium as indicated in Figure 3.41. The efficiency cost of the carbon charge is now given by trapezoid $acfg$. Again, this reflects losses in benefits to consumers from the fuel reduction, trapezoid $adeg$, less savings in production costs, rectangle $cdef$. Alternatively, it is the loss in consumer surplus, trapezoid $jlma$, less revenue gains to the government, rectangle $jlca$.

In this case the efficiency cost has two components: (i) one-half times the carbon charge (per ton of CO₂) times the overall CO₂ reduction; and (ii) the pre-existing tax per unit of fuel use, times the fuel reduction, and aggregated across fuel markets.

3.7.1.3 Efficiency costs in CPAT

The efficiency cost can be (approximately) computed by the 'Harberger triangle', that is, one-half times the carbon charge expressed per unit of fuel use times the fuel reduction. If the carbon charge is applied to multiple fuel products, the efficiency cost is the sum of Harberger triangles across the fuel markets. Equivalently, the efficiency cost is simply one-half times the carbon charge (per ton of CO₂) times the overall CO₂ reduction, which corresponds to the

integral under the marginal abatement cost (MAC) schedule where the latter is the horizontal summation of individual MAC curves for all the behavioral responses promoted by the carbon charge.

In CPAT, the efficiency costs follow the Harberger methodology, i.e., efficiency costs are treated as deadweight costs, ddw . These costs correspond to the area of the trapezoid described above, which is expressed as follows:

$$ddw_{ft} = \frac{(nc_{ft} - xcp_{ft})}{2} * (F_{P,ft} - F_{B,ft})$$

Where the first term $\frac{(nc_{ft} - xcp_{ft})}{2}$ represents the average of new and pre-existing tax, respectively denoted nc_{ft} and xcp_{ft} , and $F_{P,ft} - F_{B,ft}$ corresponds to the change in fuel consumption from the baseline to the policy scenario.

3.7.1.4 Co-benefits

If it is now supposed that there are also local air pollution or other domestic environmental costs associated with use of the fuel product as indicated in Figure 3.41. The reduction in fuel use from the carbon charge reduces these costs by rectangle $ncfo$, which corresponds to the domestic environmental co-benefits. In short, the area $acfg$ is presumably due to the externality created from fossil fuel use in the first place – and hence that is why the entire $ncfo$ area could be a benefit. The net economic benefit is defined as the domestic environmental co-benefits—excluding global climate benefits—less efficiency costs. This is shown by trapezoid $noga$, as the co-benefits exceed the efficiency cost. More generally co-benefits might offset a portion of (rather than more than offsetting) efficiency costs in which case net economic benefits are negative.

3.7.2 Energy externalities costs

Externalities are deadweight losses from the tax before revenue recycling and do not include revenue recycling and tax interaction effects. In the dashboard of CPAT, energy externality costs are calculated under the baseline scenario and include costs above the marginal cost, that is costs related to air pollution, congestion, road damage and accidents and global warming (see Figure 3.42). The sum of these externalities, including the supply costs and the potential VAT, actually defines what is called the ‘efficient price’.

These costs are displayed by fuel (i.e. coal, natural gas, electricity and liquid fuel, gasoline, diesel, LPG and kerosene) and sectors grouping (except for liquid fuels) and broken down by various components:

1. **Supply costs** as defined in the Prices section of CPAT.

Energy externalities in the baseline: by fuel in 2030, Colombia

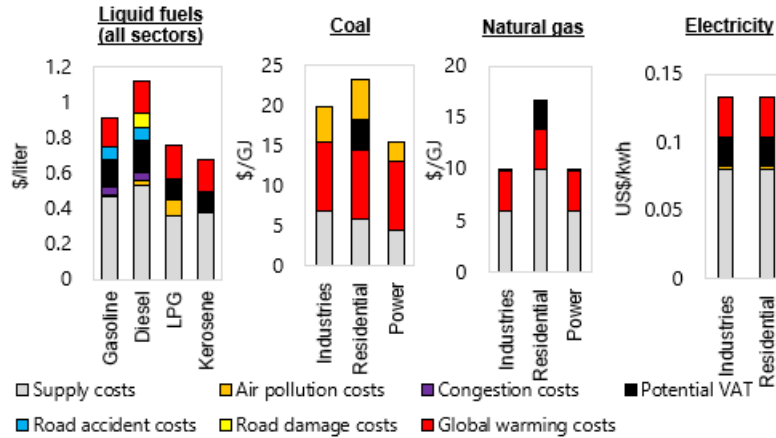


Figure 3.42: Dashboard: Global energy demand scenario

2. **Air pollution costs.** These costs are associated mortality and morbidity attributed to air pollution. Averted mortality is valued using a Value of the Statistical Life (with the method selected by the user) and morbidity, measured as years lived with disabilities, is valued using a fraction of wages. See Section 6.7 of the Air Pollution module for methodological details.
3. **Road accident costs and Congestion costs³⁷.** The main road transport co-benefits of a carbon tax are a reduction in road accidents (from a reduction in driving, changes in the vehicle fleet, less aggressive driving, etc.) and a reduction in congestion (from a reduction in driving, an increase in car sharing, changes in the vehicle fleet, changes in transport timing decisions, etc.). Externality costs are estimated based on the baseline and policy forecast (i.e. adjusted for the fuel price change using a country-specific elasticity) accidents/congestion. The monetary value of accidents (multiplying fatalities by value of statistical life) and congestion (multiplying time lost in traffic times value of travel time) is then computed. Finally, the change in value of accident/congestion is divided by the change in motor fuel consumption.
4. **Global warming costs** are by default defined at the global level. These costs are estimated based on the damage per ton CO₂ (in real USD\$ 2021) and the level of CO₂ emissions under both scenarios. Note that several social cost of carbon can be selected:
 - The damage per ton of CO₂ is by default set to a **social cost of carbon**, fixed to 75USD\$ in 2030, implying an annual rise in real terms from 2018 of the social cost

³⁷Note that road damage costs are also calculated in the Transport module. Resulting reduced road damage are currently not accounted for in welfare benefits, although they are also estimated in the Transport module (see Section 7.3.4).

of carbon of 4%.

- **Estimated social costs by Ricke et al. (2018)** for which the national social cost of carbon discount rate and elasticity of marginal utility can be modified. Note that Ricke et al. (2018) estimates are country specific. More information can be found in the tab “SCC” of CPAT.
- The social cost of carbon can also rely on the **Global US EPA estimates** with a 2.5% discount rate.
- Finally, the user can manually enter a social cost of carbon (in US\$2021 per ton of CO₂), assuming that the latter starts in year 2021.

These options can be modified in the dashboard:

Social cost of carbon (SCC) assumptions:	
Target-consistent carbon price by 2030 (for 'Target' option)	75
NSSC discount rate (ρ)	2%*
NSSC elasticity of marginal utility (μ)	1.5%*
Global social cost of carbon (GSCC) source	Target*
Manual - assumed starting in year 2021 (US\$2021 per ton of CO ₂)	50
SCC (both NSSC and GSCC) - annual rise in real terms	4%

Figure 3.43: Dashboard: Social cost of carbon (SCC) assumptions

- **Potential VAT** can be calculated on the supply cost only or on the supply cost augmented by all externalities (the default).

3.7.3 Monetized welfare benefits

CPAT provides an assessment of climate co-benefits associated with carbon pricing and fossil fuel price reform. Welfare benefits induced after the introduction of the carbon tax include the monetized following items (in real USD\$ 2021), which are estimated based on the description of the costs described in the above section:

1. **Averted climate damages (national)** is defined as the difference between the total national global warming costs in the baseline and the policy scenario.
2. **Averted air pollution mortality/morbidity** is taken from the Air Pollution module. The air pollution welfare gains are calculated from reduced mortality and morbidity attributed to improvements in air pollution. Averted mortality is valued using a Value of the Statistical Life (with the method selected by the user) and morbidity is valued as a fraction of wages. See Section 6.7 of the Air Pollution module for methodological details.

3. **Averted road accidents** are taken from the transport module and represent the change in the number of road accidents induced by the implementation of the policy selected by the user, which thus corresponds to externality benefits.
4. **Reduced congestion** is taken from the transport module. In the same vein, external benefits from reduced congestion results from the change in traffic induced by the implementation of the policy selected by the user.
5. **Efficiency costs** are defined as the deadweight costs resulting from the carbon tax (i.e. the average of existing and new carbon tax introduced) and the change in fuel consumption for each fuel considered, including electricity.

CPAT dashboard shows monetized net welfare benefits as percentage of GDP (see Figure 3.44).

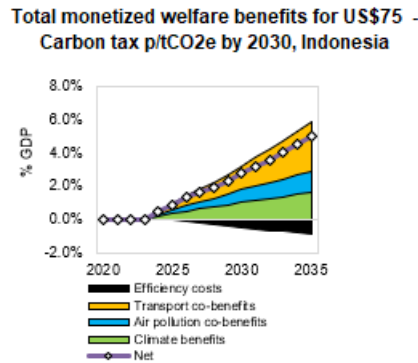


Figure 3.44: Dashboard: Total monetized welfare

3.8 Validation

3.8.1 Overview

It is important to note that the validation exercise differs from the calibration. While the calibration performed for some variables throughout the mitigation module prevents the model from deviating from observed data (i.e. for 2019 to 2021), particularly in the context of COVID-19, the validation analysis covers a broader time horizon and aims to explore how the mitigation module performs against other models or to compare it against the literature. The analysis also includes sense-checking and parameter sensitivity analysis of the parameters defined in the mitigation module. The validation is organized as follows:

1. **Elasticities estimations.** As CPAT is mainly driven by elasticities with respect to prices and economic activity, an econometric analysis is carried out to compare the elasticities used in CPAT and those obtained from an empirical analysis.

2. **Comparison of CPAT against other models.**
3. **Ex-post studies.** This section presents the literature’s estimates of the effectiveness of carbon pricing with respect to emissions and compares them to the CPAT results.
4. **Hindcasting.** The hindcasting exercise aims at testing CPAT’s forecasts against observed data. It searches to evaluate the performance of the used assumptions when trying to reproduce historical information.
5. **Parameter Sensitivity Analysis.** The analysis explores the sensitivity of a set of selected parameters.

Before deep diving into the validation analysis, a first step in the validation process is performed to ensure that CPAT produces reliable data, especially for the data fed into the rest of the validation analysis. To further validate CPAT and check its functionality for all countries the T and Tt scenarios have been created in the Multiscenario Tool to test 826 parameters used in CPAT. The T-scenarios use average power models and show how CPAT behaves under different carbon taxation and how these parameters change. There are six testing scenarios:

1. **T0-T6**, when T0 has no carbon tax;
2. **T1** (small carbon tax scenario) introduces 12\$ carbon tax with 20\$ target carbon tax;
3. **T3** (medium carbon tax scenario) introduces 36\$ carbon tax with 60\$ target carbon tax;
4. **T6** (high carbon tax) introduces 120\$ carbon tax with 200\$ target carbon tax; and
5. **The T2, T4 and T5** introduce intermediate rates for comparison.

In addition to these scenarios, the scenarios denoted Tt (i.e. T0t-T6t) use engineer model instead of Average power models and hold the same assumptions and carbon tax rates as the T scenarios described above (i.e. T0-T6). In order to test CPAT, the following steps were performed:

1. **Settings.** The T0-T6 use average model, while T0t – T6t scenarios use engineer model.
2. **Model runs.** The MT is run using the same defaults.
3. **Data.** The database is then compiled, retaining CPAT’s output on 826 parameters for 218 countries.

The scenarios aim to provide data for further Parameter Sensitivity, hindcasting and comparison analysis, as well as signal any problems with country specific results, i.e. due to the poor data quality. Based on the outcomes, we classify countries into working and ones which produce spurious results. The Table on Countries coverage presented in the User Guide results from this testing.

3.8.2 Panel estimation of energy demand

3.8.2.1 Introduction

This section describes the results from the estimation of some of the fuel demand equations incorporated in CPAT. The aim is to

- Deliver an empirical view of the elasticities with respect to price and economic activity;
- Establish the size and direction of any linear trend in fuel consumption; and
- Reflect on the difference between the value of the elasticities and trends estimated in this study and those currently used in CPAT.

Elasticities describe the percentage change in a dependent variable in response to a percentage change in an independent (driving) variable. As an example, a price elasticity equal to -0.3 implies that a 100% increase in the price delivers a 30% reduction in fuel consumption. In the case of models using data undergoing a logarithm transformation, the elasticity with respect to a given variable is simply the estimated coefficient on that variable.

3.8.2.2 Methodology

The approach used here reflects underlying CPAT model and database structure in relation to:

- **Frequency of data and timespan.** In the estimation we used annual data ranging between 2000 and 2018, i.e. the dataset currently incorporated in CPAT. This is a panel dataset in which information for a set of fuels consumed in a set of sectors (and their driving variables) is observed across time and countries (here taken as the unit dimension of the panel).
- **Driving factors.** Consumption of a fuel in a specific sector is assumed to be a function of fuel price (in that sector) and of the overall level of economic activity (as measured by the GDP), with both variables expressed in real terms.
- **Static functional form.** The whole impact of a change in a driving variable, say, price, unfolds within the year covered by that observation. This means that last year's prices have no impact on this year's and future consumption.
- **Sectorial disaggregation.** Results are reported based on the disaggregation underlying the current set of elasticities in CPAT (industrial, service, residential and transport) but data are available for a number of industrial subsectors and transport modes (as shown in Appendix B - Energy balances, Figure 3.77) which are used in the estimation. This implies that we are able to produce estimates for the elasticities of a fuel consumed in any industrial subsector, so that the range of these estimates for the industrial sector as a whole is indicated as with a boxplot in Figure 3.45 and Figure 3.46.

- **Fuel disaggregation.** Results are reported based on the fuels underlying the current set of elasticities in CPAT (coal, electricity, natural gas, other oil products, biomass, diesel and gasoline). In the case of other oil products, we are able to rely on two fuels in the estimation: kerosene and lpg.

We estimated the fuel demand below for each combination of sector and fuel for which estimation was deemed relevant and feasible:

$$\ln f_{c_{it}} = \alpha_i + \beta_1 \ln y_{it} + \beta_2 \ln p_{it} + \beta_3 t + \epsilon_{it},$$

where $f_{c_{it}}$ indicates the consumption of a specific fuel at time t in country i in a specific sector, p_{it} indicates the price for that fuel and y_{it} the overall level of GDP in the country. There are no indices in relation to the sector and the fuel in the equation as estimation is conducted for each combination of fuels and sectors. The individual effects α_i reflect constant (across time) factors which affect fuel consumption in a specific sector in a specific country given the value of the independent variables in the model. An example for these factors could be energy efficiency policies affecting fuel consumption regardless of the level of economic activity and price. Finally, t is a linear time trend. We also introduced a time effect λ_t but it was never found to be statistically significant when a linear trend was also included.

In terms of relevance, we excluded sectors for which the CPAT dataset contained data covering less than 0.5 GTOE while in terms of feasibility we required a minimum of about 300 observations for a sector-fuel combination to be included in the analysis. As a consequence, the number of units (countries) used in the analysis varied from more than 150 in the case of gasoline used for road transport to 13 in the case of coal used for non-energy use or otherwise not included in other industrial subsectors.

3.8.2.2.1 Adopted estimators

The following estimators were implemented: 1) the between estimator (BE); 2) the pooled OLS estimator (POLS) and; 3) the Common Correlated Effects Mean Group (CMG) estimator of M. Hashem Pesaran (2006). The results from the Between and Pooled OLS estimator are reported only for those cases when they produce consistent estimates, ie. when regressors are not correlated with individual effects as assessed by the Hausman test. The choice of these estimators was motivated by the aim of assessing the long-term impact of driving factors on fuel consumption - despite the use of a static functional form in CPAT - and evidence of Cross-Sectional Dependence (i.e. correlation across the units in a panel dataset).

More precisely, the choice of adopting these estimators is motivated by the following considerations:

- The BE produces consistent estimates of long-run coefficients for a panel with adequate number of observations across time and units (in our case countries) as formally discussed in M. Hashem Pesaran and Smith (1995a). It also produced the best estimate of long-run

price coefficient for gasoline in the Monte Carlo simulation discussed in Badi H. Baltagi and Griffin (1984a), although estimates from POLS were not markedly different.

- The POLS produced the most robust forecasts (assessed based on the RMSE) in the Monte Carlo study in Badi H. Baltagi and Griffin (1984a). In the same study, the BE produced very similar results, although with (slightly) higher errors.
- The CMG estimator produces unbiased estimates when cross-sectional dependence (CSD), which was assessed based on the test in M. Hashem Pesaran (2015), is correlated to included regressors in the model. We used robust standard errors (Beck and Katz (1995); Driscoll and Kraay (1998)) to take into account cross-sectional dependence but this is a valid approach only if the unobserved factors responsible for correlation across units are not correlated to variables in the model, in our case fuel price and GDP. Although the CMG estimator is robust to any form of Cross-Sectional Dependence, the extent to which it captures long-term impact of driving variables in a static model is not clear.

Two versions of the equation above are implemented in the case of the POLS and CMG estimators: one with a global linear trend, one with a trend allowed to vary across countries. Considering the number of estimates we obtain we report only those which were statistically significant at the 10% level and conform to economic theory, e.g. positive elasticity on economic activity and negative on the fuel price.

3.8.2.2.2 Data

Data used in this study reflects the dataset underlying CPAT. This means using:

- fuel consumption data from IEA energy balances;
- nominal GDP data from the IMF World Economic Outlook (WEO) database converted into real terms by using the Consumer Price Index (CPI) also from IMF's WEO;
- nominal fuel prices data from IMF's database, also converted into real terms by using the CPI index.

All the variables were converted into logarithms before the estimation.

3.8.2.3 Results

3.8.2.3.1 Price elasticities

Figure 3.45 compares the estimates of price elasticities obtained here with those used in CPAT for the transport (quadrant A), residential (quadrant B), industrial (C) and service sector (D). Estimated elasticities are similar to those used in CPAT in the case of the:

- residential sector, with the exception of electricity for which we estimated -0.1 - considerably lower than the -0.4 value used in CPAT;

- industrial sector, with the exception of diesel for which CPAT uses the high value of -1.1.

Difference between the elasticity in CPAT (-0.61) and the value estimated here (-0.19) for gasoline in the transport sector might be related to the fact that only the estimate from the CMG estimator can be used in the comparison with CPAT. Low estimates for price elasticities of gasoline in road transport are however very established in the literature. A recent survey, Miguel Galindo et al. (2015), indicated -0.10 and -0.30 for short- and long-term elasticities, respectively, with our estimate (-0.19) falling right in the middle of this range.

The difference between elasticities estimated here and those used in CPAT is noticeable in the case of the Service sector. CPAT postulates fuel consumption being more price responsive than demand in industrial sector while our estimates point at elasticities being similar to those estimated in the residential sector. Assuming that there is considerable overlap between fuel uses in the service sector and in households (space heating, air conditioning and everyday electrical appliances), our findings of similar elasticities in the service and the residential sector seem plausible. Considering the difference between our estimates and CPAT and the growing importance of the service sector globally, this is a topic which should be explored further in the next iteration of CPAT.

3.8.2.3.2 Elasticities with respect to economic activity

Figure 3.46 compares the estimates of the elasticities with respect to economic activity with the values used in CPAT for the transport (quadrant A), residential (quadrant B), industrial (C) and the service sector (D). Estimated elasticities are similar to those in CPAT in the case of the:

- residential sector, with the exception of electricity for which we estimated a relatively low (0.16) value compared to the value (0.65) used in CPAT;
- industrial sector, with the exception of natural gas for which CPAT uses a value of 0.81 while estimates here range between 0.33 and 0.56.

Differences still emerge in the transport (quadrant A) and in the service sector (quadrant D). With regard to the former, our estimates (ranging between 0.31 and 0.53 across fuels) are close to the results from the meta-analysis in Miguel Galindo et al. (2015) indicating short- and long-run income elasticities equal to 0.26 and 0.46, respectively. CPAT is currently using the higher value of 0.57 for gasoline and 0.65 for other oil products. With regard to the service sector, CPAT incorporates a stark difference between elasticities for biomass and diesel (with values up to 0.41) and those for electricity and natural gas (with elasticity as high as 0.9). In contrast, our estimates are more homogeneous across fuels with values at most as high as 0.7.

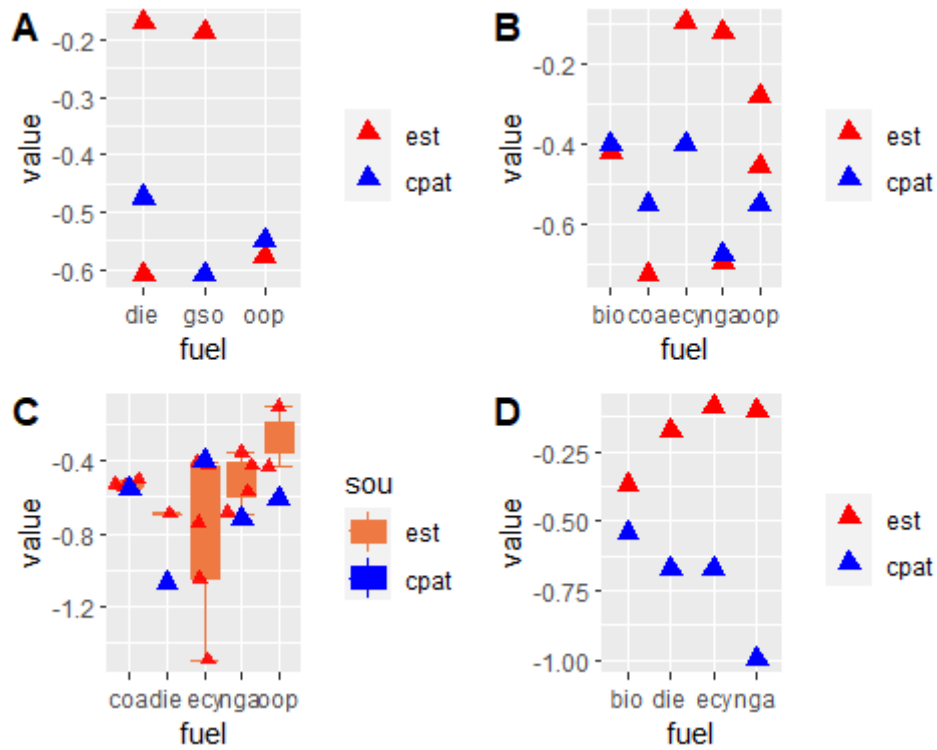


Figure 3.45: Comparison between price elasticities used in CPAT and those estimated in this study for transport (A), residential (B), industrial (C) and service (D) sectors. The red triangles indicate an estimate obtained from one of the adopted estimators, while the blue triangles indicate the value of the elasticity used in CPAT. The boxplot in subplot C indicates the range of the estimates obtained for the industrial subsectors included in the study.

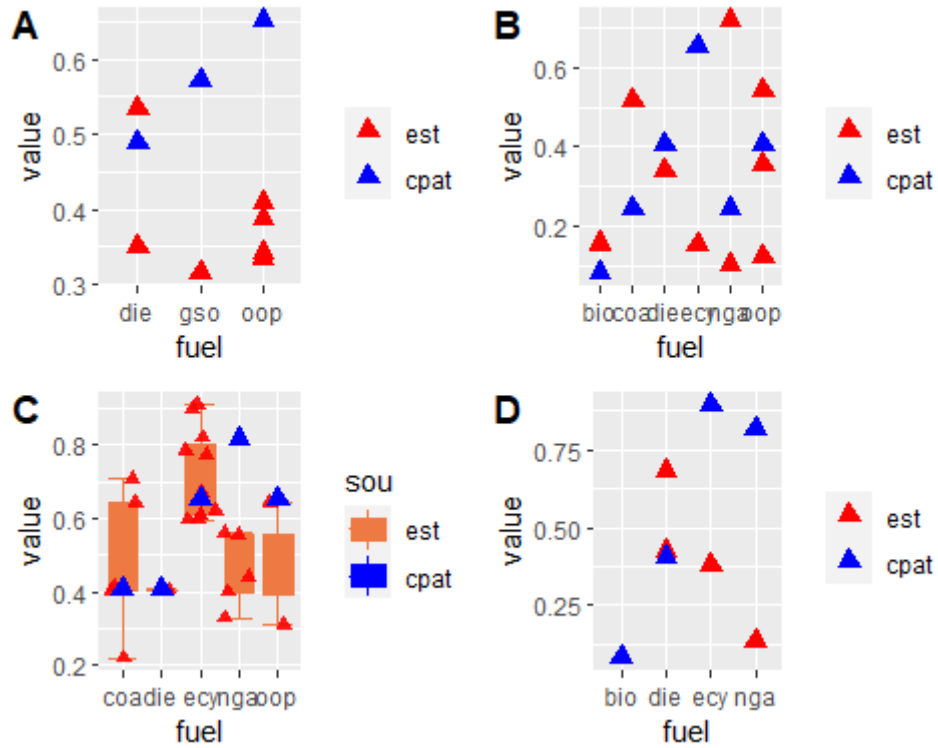


Figure 3.46: Comparison between income elasticities used in CPAT and those estimated in this study for Transport (A), Residential (B), Industrial (C) and Service (D) sectors. The red triangles indicate an estimate obtained from one of the adopted estimators, while the blue triangles indicate the value of the elasticity used in CPAT. The boxplot in subplot C indicates the range of the estimates obtained for the industrial subsectors included in the study.

3.8.2.3.3 Linear trend

CPAT includes a term called “annual autonomous improvement in efficiency” which conveys the annual percentage reductions in fuel consumption due to increasing energy efficiency. The intensity of this factor is stronger in the case of transport (average of about -0.5% across fuels) compared to the other sectors for which average for each fuel varies between -0.27 and -0.06%

Our estimate of a global linear trend for the sector-fuel combinations included in this study presents quite a different picture, as a negative trend in consumption could be estimated only for coal and other oil products. In the case of biomass, electricity and natural gas the trend is positive. In the case of diesel and gasoline consumption in the transport sector, not reported in Figure 3.47, the estimated models pointed out at non-statistically significant linear trend.

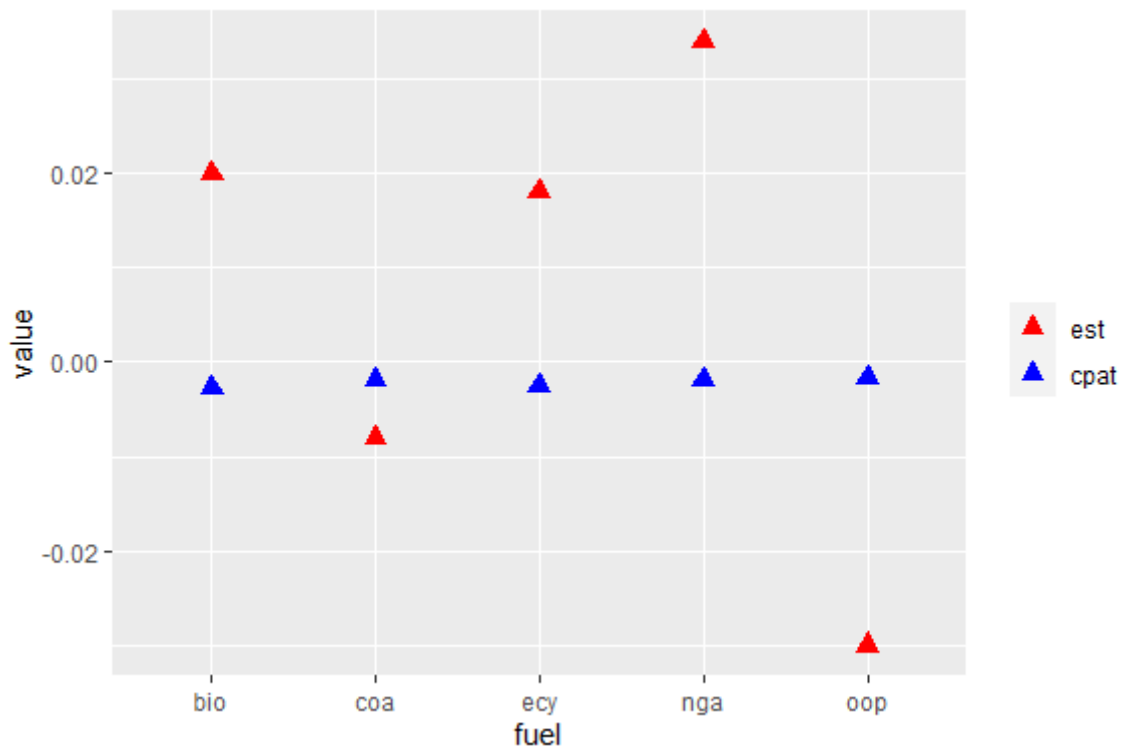


Figure 3.47: Comparison between the assumed annual autonomous improvement in efficiency in CPAT and the global linear trend estimated in this study. The red triangles indicate the average of the estimates from the models allowing for a global linear trend.

3.8.2.4 Conclusions and areas for improvement

The empirical validation pointed out that the elasticities with respect to price and economic activity in CPAT tend to be on the same ballpark as those estimated here, with some exceptions mainly related to road transport and the service sector.

This exercise pointed out that estimated global linear trends are considerably different from the assumed impact of energy efficiency used in CPAT. With hindsight, this is not surprising, as estimated global linear trends include the impact of energy efficiency but also changing preferences for a specific fuel or the impact of changing sector decomposition. As an example, one would expect a positive linear trend in the case of biofuels in the transport sector due to the impact of policies facilitating substitution away from fossil fuels to renewable sources. CPAT might benefit from continuing to disentangle the perceived impact of energy efficiency (as currently done) especially if that coefficient could be linked to explicit policymaking.

This empirical validation has provided an opportunity for a thorough assessment of CPAT and how econometric analysis may inform values used in the model. This resulted in a number of considerations that will be explored in the next iteration of model development. In particular, CPAT is likely to benefit from including:

- Elasticities estimated on an extensive dataset spanning about 4 decades which has been recently put together. Although this is a key development allowing the implementing of more sophisticated approaches and functional forms described below, as a first step, it seems helpful to focus on the estimators considered in this note.
- A more focused measure of economic activity. The use of GDP to measure economic activity for each sector included in CPAT is not supported by best practice in the energy literature and involves the risk of producing unstable estimates, and therefore forecasts. As an example, if the share of a sector's economic activity in the whole economy changes in a specific direction, CPAT would under- or over-forecast fuel consumption in that sector. As historical data for more focused economic activity indicators are available for all sectors in CPAT, one would need to assess whether one could obtain forecast time series which are needed by the model to make this approach feasible.
- A more explicit treatment of long-run estimates. CPAT can incorporate the long-run / short-run distinction explicitly through an Error Correction Model (ECM) specification which is included in the macro-economic model of the World Bank or - perhaps more simply
 - maintain its current specification but include two sets of elasticities, one for long-run and the other for short-run forecasts, with the timing of the switch between the two informed by empirical evidence.
- A more explicit analysis of the impact of cross-price elasticities. This is a very important factor for a model assessing consumption for each fuel like CPAT. Systematic approaches

to fuel substitution bring their own set of challenges (see Agnolucci and De Lipsis (2020)), to the extent that a simpler ad-hoc method may be preferable at least as a starting point, perhaps focused only on the substitution of specific fuels in specific sectors.

- Exploring feedback mechanisms between the variables incorporated in the model and their possible endogeneity. This does not seem a considerable concern considering the variables currently used in CPAT but may deserve its own empirical exploration if more focused indicators of economic activity (as consequence of point 2 and more likely to be endogenous) are used in the model.
- Assessing the extent to which elasticities vary across sectors and countries. The current version of CPAT includes the possibility of differentiating elasticities with respect to price and economic activity based on whether a sector is in a country belonging to the Lower Income, Lower Middle Income and Upper Middle-Income group on one side, and High-Income Country. The next phase of model development should thoroughly explore this possible source of heterogeneity alongside other sources, e.g. the possibility of allowing heterogeneous responses across industrial subsectors.
- Trying to disentangle the impact of energy efficiency from changing preferences for a specific fuel, either through variables related to explicit policymaking or incorporating evidence from specific policy events

3.8.2.5 References

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3.8.3 Model comparisons

Over the current section, we will compare CPAT results and projections with other models over a selection of indicators. We will therefore:

1. Compare CPAT's baseline results against Enerdata and the IEA,³⁸
2. Assess the sensitivity to carbon price against the Enerdata POLES model;
3. Put the two together: compare CPAT time trend for different carbon prices vs alternative models.
4. Explore the power sector results compared against selected results from EPM

3.8.3.1 Baseline validation

This section is dedicated to the assessment of the CPAT baseline results. The latter is observed and compared with other models/sources through time series. We use two sources for comparison. The first and main source used is the Stated Policies (STEPS) scenario of the IEA World Energy Outlook 2021, extracted from RFF's Global Energy Outlook 2022 database. The second source used for comparison is Enerdata's long-term Marginal Abatement Cost Curves (MACC).

In both cases, the comparison is established based on specific indicators available in the different datasets (from Enerdata and from the IEA). We will therefore challenge both Average and Engineer models of CPAT.

3.8.3.1.1 Comparison with the STEPS scenario of the IEA

The IEA's STEPS scenario reflects current policy settings based on a sector-by-sector assessment of the specific policies that are in place, as well as those that have been announced by governments around the world.

Data for solar has been added manually from the IEA WEO 2021 as it was not included originally in the RFF dataset.

We only have 3 points of data from the IEA: 2019, 2020, and 2030. The indicators selected are: Total CO2 emissions, Primary energy consumption by fuel, and Electricity generation by fuel.

Overall, the comparison shows comparable results between CPAT and the IEA STEPS scenario. Indeed the figures below suggest outcomes of same order of magnitude for the observed year (i.e. 2019, 2020 and 2021) and long-term projections are similar (see Figure 3.48).

³⁸Note that additional comparisons are available on demand. Notably, additional comparisons were done disaggregating the results per country, per sector and per fuel when available.

World energy related CO2 emissions comparison

CPAT average & engineer models vs. IEA WEO 2021 - STEPS Scenario via RFF-GEO, mtCO2

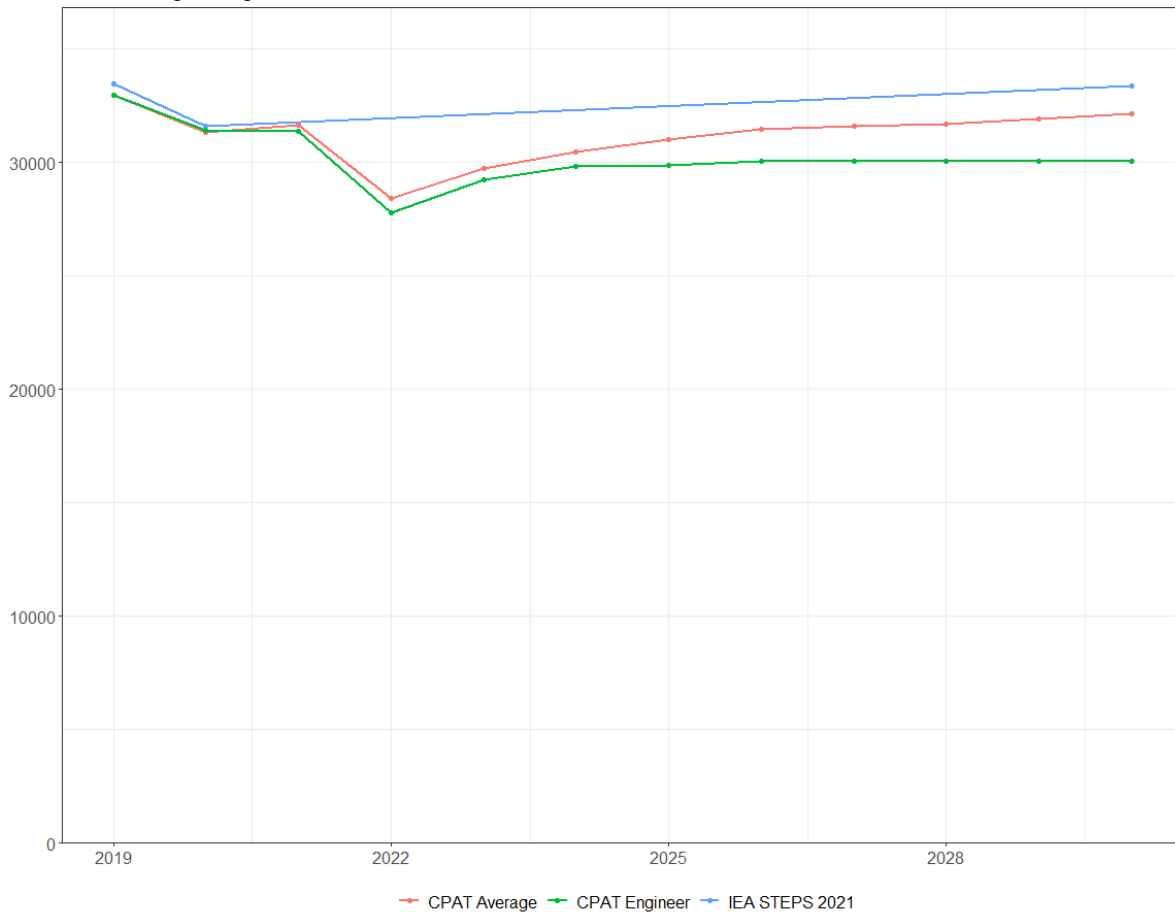


Figure 3.48: World energy related CO2 emissions comparison

Note that it is not possible to observe the inflection point in 2022 in the IEA projection, as data point for the year 2022 is not available. As defined by RFF, Primary energy consumption displays the estimated energy content of fuels consumed prior to any conversion process.

World primary energy consumption comparison

CPAT average & engineer models vs. IEA WEO 2021 - STEPS Scenario via RFF-GEO, Gtoe

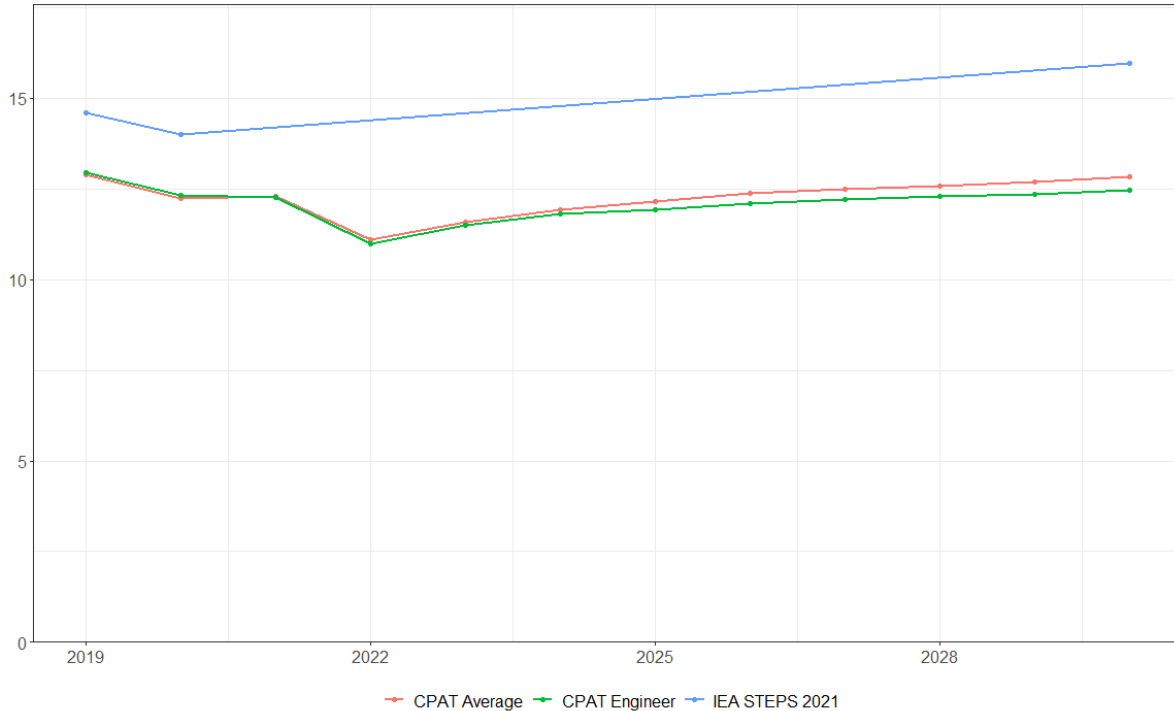


Figure 3.49: World primary energy consumption comparison

Oil in CPAT is the aggregation of Diesel, Gasoline, LPG, Kerosene, and Other Oil Products. A different aggregation could explain the difference observed in order of magnitude for Oil.

In Europe and Eurasia, discrepancies are mainly driven by the results of Russia (see Figure 3.51). It is important to note that there is no data for Solar Electricity Generation per country in the RFF-GEO dataset for the IEA STEPS scenario. Strong divergence should be noted between the two models on the nuclear generation.

3.8.3.2 Carbon Price Sensitivity

The sensitivity analysis is the observation of the evolution of the emissions depending on the carbon tax level. We will use the data from Enerdata in order to establish the analysis. We are taking into account both Average and Engineer models of CPAT. The graphs are indexed on the baseline scenario, as a 100% of emissions.

World primary energy consumption comparison by fuel

CPAT average & engineer models vs. IEA WEO 2021 - STEPS Scenario via RFF-GEO, Gtoe



Figure 3.50: World primary energy consumption comparison by fuel

Regional electricity generation comparison

CPAT average & engineer models vs. IEA WEO 2021 - STEPS Scenario via RFF-GEO, TWh

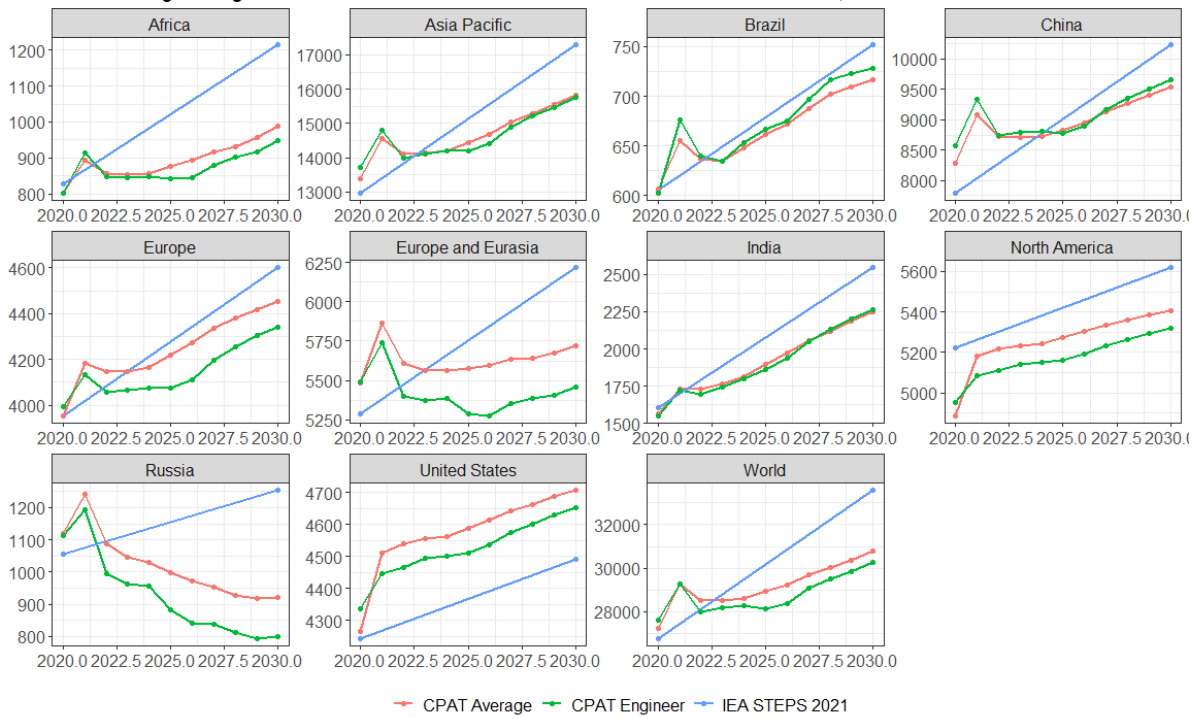


Figure 3.51: Regional electricity generation comparison

Electricity generation comparison by fuel in World

CPAT average & engineer models vs. IEA WEO 2021 - STEPS Scenario via RFF-GEO, TWh



Figure 3.52: Electricity generation comparison by fuel in World

We will only consider 3 indicators: Total CO2 emissions, Energy related CO2 emissions - Power sector, and GHG emissions, exc. LULUCF. The focus is at the world level, for the year 2030. We see good alignment between the two models for all three indicators and both CPAT power model choices (average or engineer).

Note here we abstract for any differences in baseline. See the previous and next sections for that topic.

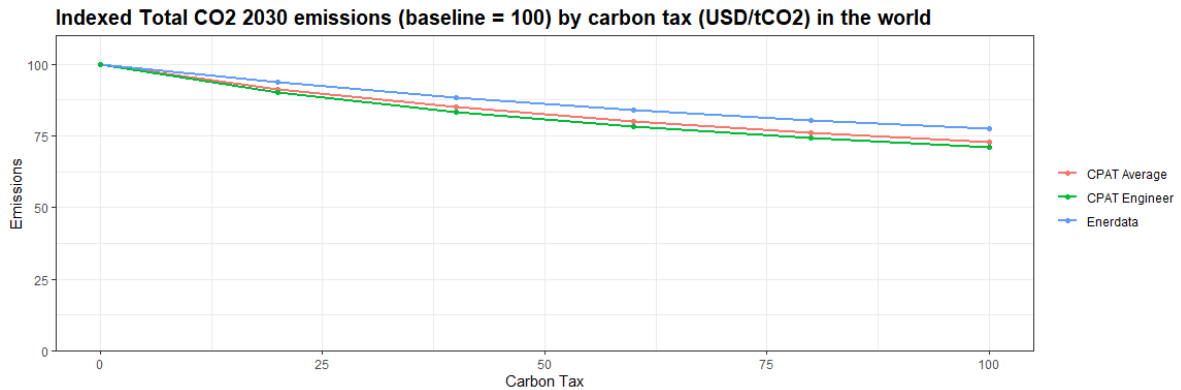


Figure 3.53: Total CO2 emissions

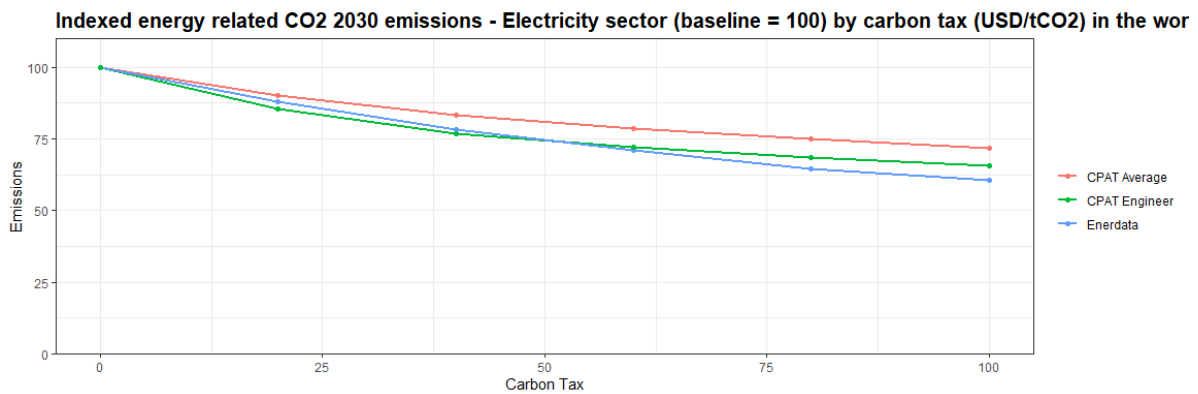


Figure 3.54: Energy related CO2 emissions - Power sector

3.8.3.3 Comparison with Enerdata's long-term Enerbase scenario

It should be noted that Enerdata's scenarios were formed before the Covid crisis.

This comparison is based on different carbon tax scenarios (including the baseline scenario), target for 2030: 0 USD/tCO2, 20 USD/tCO2, 40 USD/tCO2, 60 USD/tCO2, 80 USD/tCO2, 100 USD/tCO2, and 120 USD/tCO2. These scenarios are computed using the average and

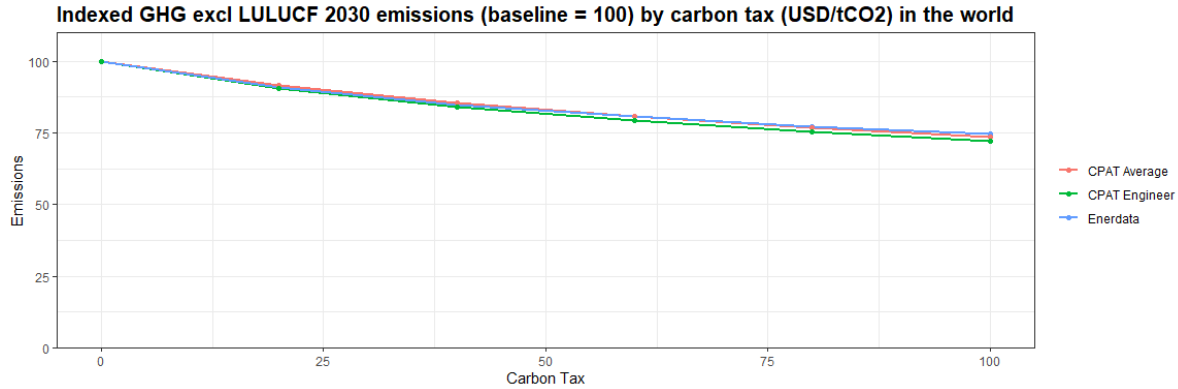


Figure 3.55: Total GHG emissions, exc. LULUCF

the engineer models of CPAT in order to add another layer of comparison. Enerdata presents CO₂ MACC, which is going to be used as an equivalent to the target carbon tax. There are 3 points of data: 2025, 2030 and 2035.

We consider 5 indicators: Total CO₂ emissions, Energy related CO₂ emissions - Power sector - Industry - Buildings - Transportation, and GHG emissions, exc. LULUCF.

Results show comparable results, with both models having similar slopes. Enerdata's outcomes are, however, higher and aligned with pre-covid results of CPAT, suggesting that the COVID-19 adjustment implemented in CPAT may explain the difference. In addition, it is worth mentioning that CPAT is calibrated on IEA's data in the year 2019 to 2021, and IEA's assumptions are less conservative than Enerdata when it comes to the share of coal power plant in the future.

Overall, CPAT's results are similar to Enerdata's results. With a few exceptions, the figures below report a similar order of magnitude and comparable directions. In this comparison, the average power model of CPAT provides closer estimates to Enerdata's scenarios.

The figures below compare CPAT's **GHG emissions (exc. LULUCF)** against Enerdata's results. Similarly, outcomes are very close worldwide, although some discrepancies are observed in some regions.

3.8.3.4 Power sector comparison vs. EPM

The power sector validation is made using the World Bank's EPM model. The World Bank's Electricity Planning Model (EPM) is a long-term, multi-year, multi-zone capacity expansion and dispatch model. The objective of the model is to minimize the sum of fixed (including annualized capital costs) and variable generation costs (discounted for time) for all zones and all years considered, subject to:

Total CO2 emissions, all scenarios

CPAT average & engineer models vs. Enerdata in the world, mtCO2e

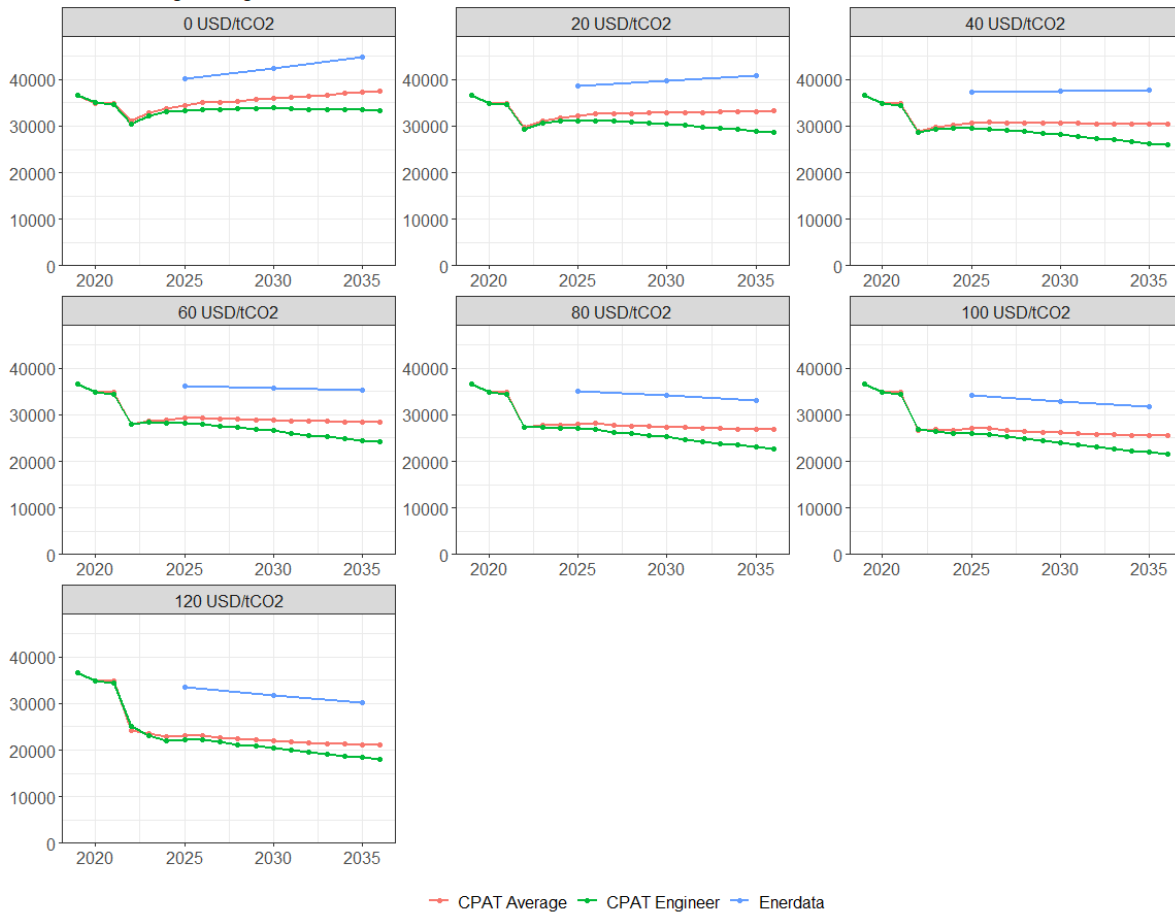


Figure 3.56: Total CO2 emissions, all scenarios

Total CO2 emissions, \$0/tCO2 in 2030 scenario

CPAT average & engineer models vs. Enerdata per region, mtCO2e



Figure 3.57: Total CO2 emissions, 0 USD/tCO2 in 2030 scenario

Total CO2 emissions, \$100/tCO2 in 2030 scenario

CPAT average & engineer models vs. Enerdata per region, mtCO2e



Figure 3.58: Total CO2 emissions, 100 USD/tCO2 in 2030 scenario

Energy related CO2 emissions - Electricity, all scenarios

CPAT average & engineer models vs. Enerdata in the world, mtCO2e

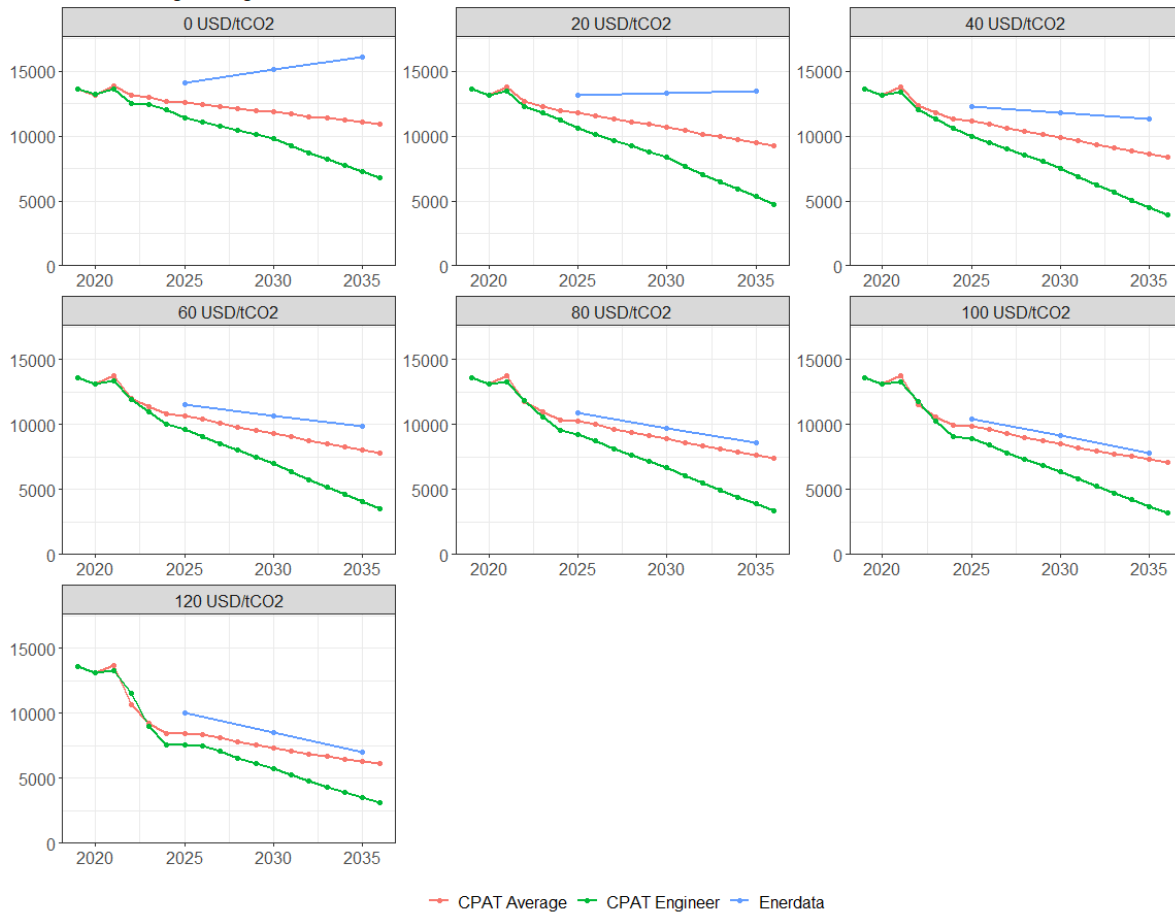


Figure 3.59: Energy related CO2 emissions - Electricity, all scenarios

Energy related CO2 emissions - Electricity, \$0/tCO2 in 2030 scenario

CPAT average & engineer models vs. Enerdata per region, mtCO2e

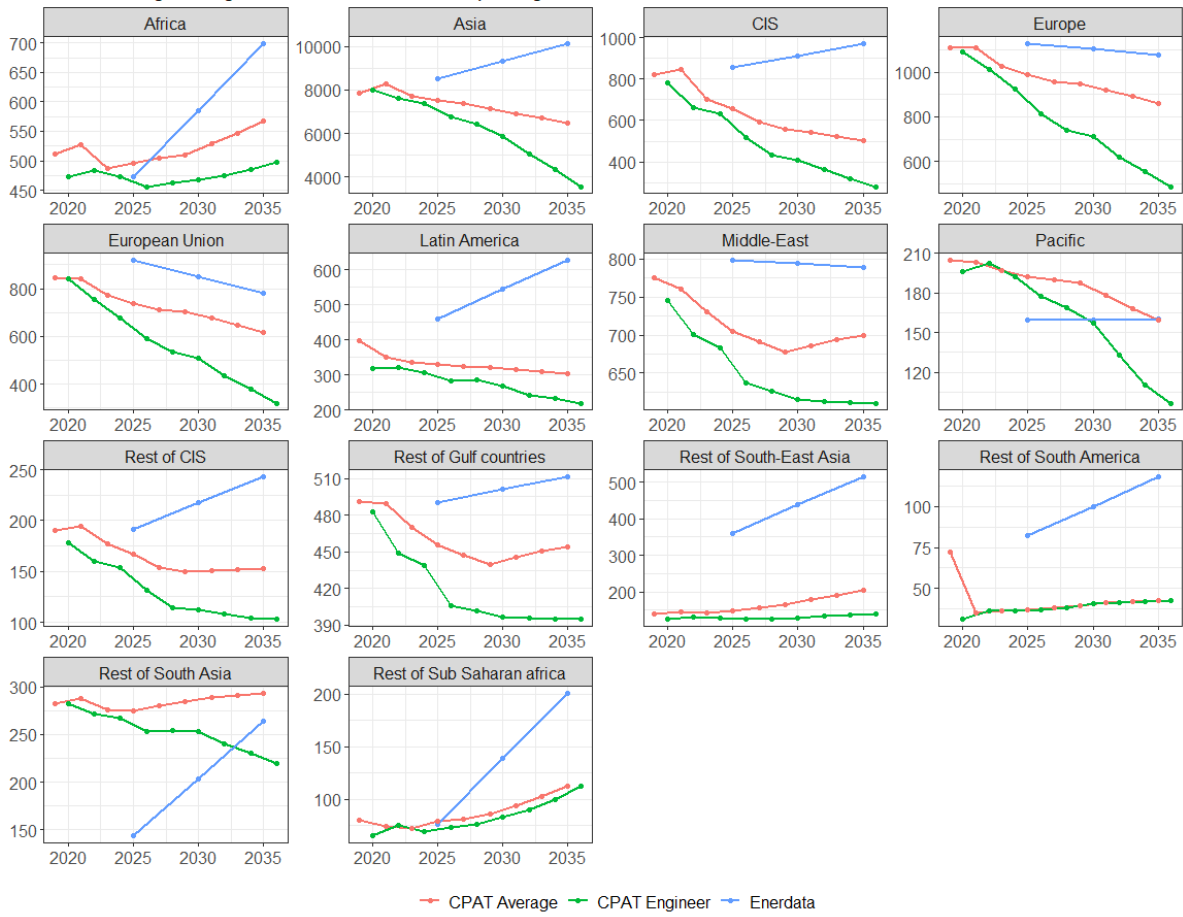


Figure 3.60: Energy related CO2 emissions - Electricity, 0 USD/tCO2 in 2030 scenario

Energy related CO2 emissions - Electricity, \$100/tCO2 in 2030 scenario

CPAT average & engineer models vs. Enerdata per region, mtCO2e

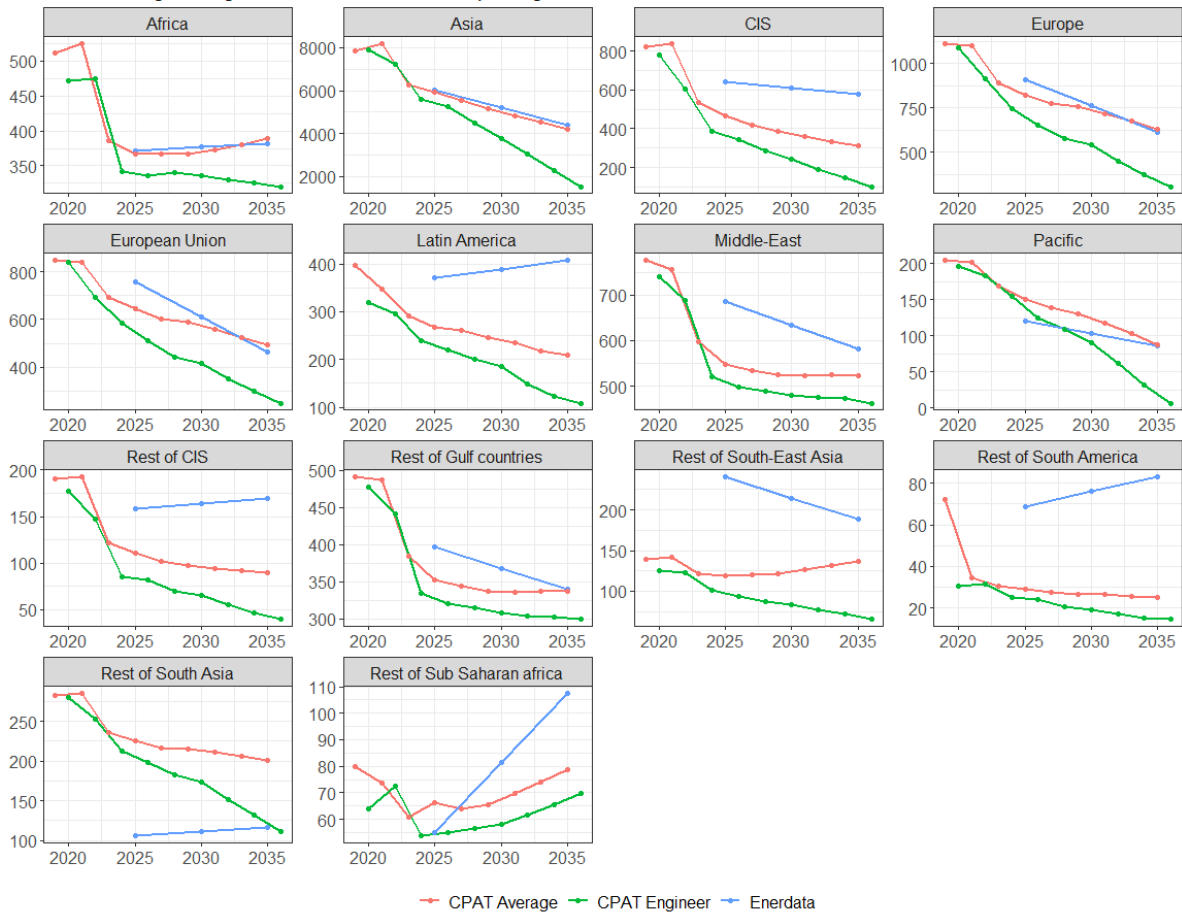


Figure 3.61: Energy related CO2 emissions - Electricity, 100 USD/tCO2 in 2030 scenario

GHG excl LULUCF emissions, all scenarios

CPAT average & engineer models vs. Enerdata in the world, mtCO₂e

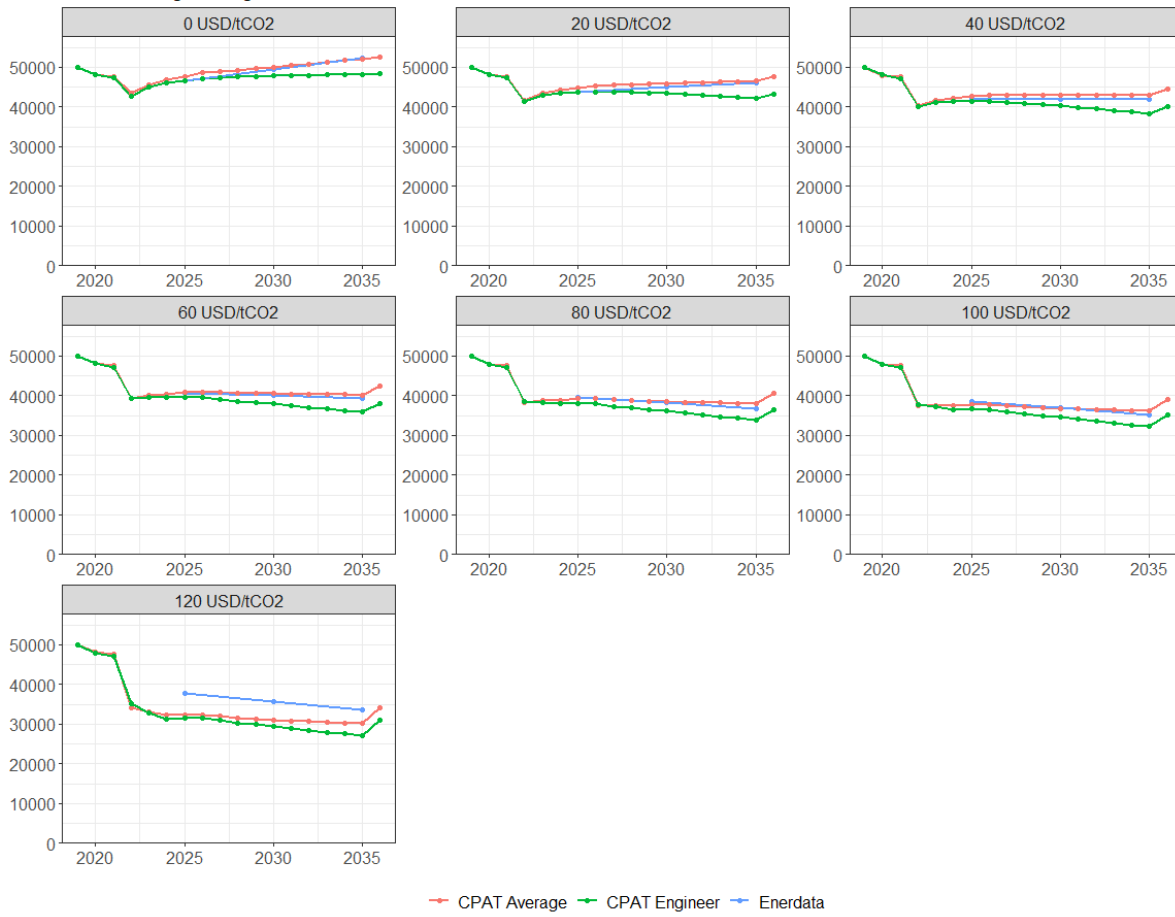


Figure 3.62: GHG excl LULUCF emissions, all sectors

GHG excl LULUCF emissions, \$0/tCO2 in 2030 scenario

CPAT average & engineer models vs. Enerdata per region, mtCO2e



Figure 3.63: GHG excl LULUCF emissions, 0 USD/tCO2 in 2030 scenario

GHG excl LULUCF emissions, \$100/tCO2 in 2030 scenario

CPAT average & engineer models vs. Enerdata per region, mtCO2e

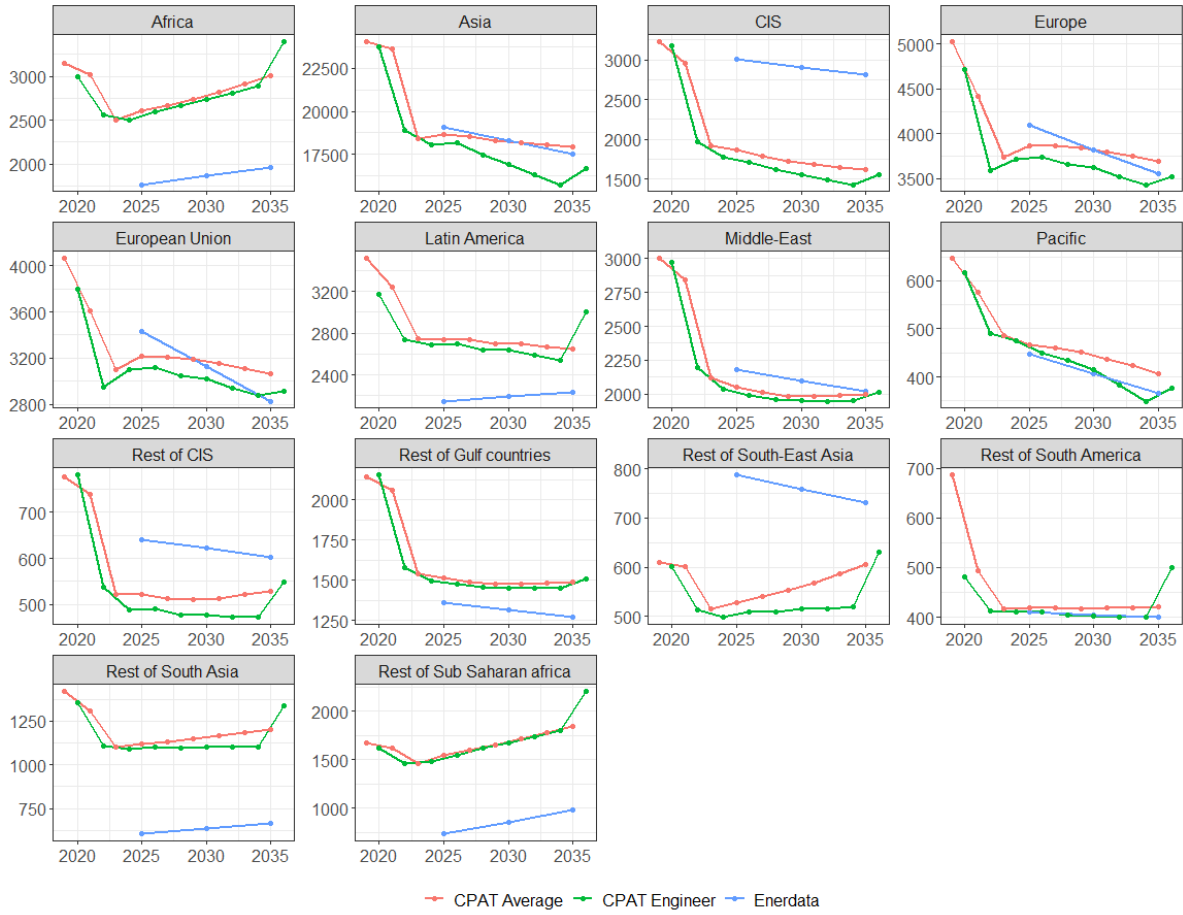


Figure 3.64: GHG excl LULUCF emissions, 100 USD/tCO2 in 2030 scenario

- Demand equals the sum of generation and non-served energy
- Available capacity is existing capacity plus new capacity minus retired capacity
- Generation does not exceed the max and min output limits of the units
- Generation is constrained by ramping limits
- Spinning reserves are committed every hour to compensate forecasting errors
- renewable generation constrained by wind and solar hourly availability
- Excess energy can be stored in storage units to be released later or traded between the other zones
- Transmission network topology and transmission line thermal limits

The model is an abstract representation of the real power systems with certain limitations. EPM is used mostly to perform least cost expansion plans as well as dispatch analyses.

3.8.3.4.1 Objectives

The main objective of this analysis is to validate the accuracy of the CPAT results by comparing them with selected results from the EPM model, for different countries. The following outputs are compared:

- Electricity Demand
- Electricity Generation
- New Investments

3.8.3.4.2 Methodology

The EPM model presents several different scenarios per country. Each scenario is defined by a 2030 carbon budget, most of the time defined as a 40% emission reduction relative to the BAU scenario. However, while the carbon budget is an input for the EPM model, it is an output for CPAT. Therefore, we used a goal seek in order to define a 2030 target carbon price in CPAT, which brought us to \$40 t/CO₂. This is an only approximately equivalent comparison: exact matching was difficult.

We use the Engineer model of CPAT for the entire comparison.

3.8.3.4.3 Caveats

Please note the following caveats on the approach followed:

- EPM has a constraint in emissions and look to 2040 (80% emission reduction relative to BAU on average), but we work with 2030. In other words, we use a proportional ratio to set the target goal seek.

- The fuel classification in CPAT does not exactly match the EPM ones. Therefore EPM “Fuel oil” will be considered as CPAT “Other oil products” (“Oil” in the legend), EPM “Onshore wind” and “Offshore wind” will be considered as CPAT “Wind”, and EPM “Geothermal” as CPAT “Other RE”. Storage is invested in CPAT but not reported so we do not compare it here.
- CPAT’s New Investments (MW) are considered spreaded in time, which explains their continuous aspect.

3.8.3.4.4 Comparison

The comparison in terms on types of fuels in the energy mix and the order of magnitude of the shares reflect similar results. It is worth noting that the EPM model shows a higher share of wind in the electricity generation for some countries (e.g. Vietnam).

It is however more complicated to establish parallels in the case of developing countries, as EPM can suggest discontinuous generation/investments.

3.8.3.4.5 Graphs

The following pages show, for a number of mostly African countries available in the EPM dataset, comparisons for the larger countries between CPAT and EPM of:

1. Overall electricity demand.
2. Electricity generation by generation type.
3. New investment by fuel type.

Comparison for a bigger set of countries, including smaller countries than previously, are available in the Appendix H (Section [3.9.8](#)).

3.8.3.4.6 Electricity Demand Comparison

Electricity demand

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), TWh

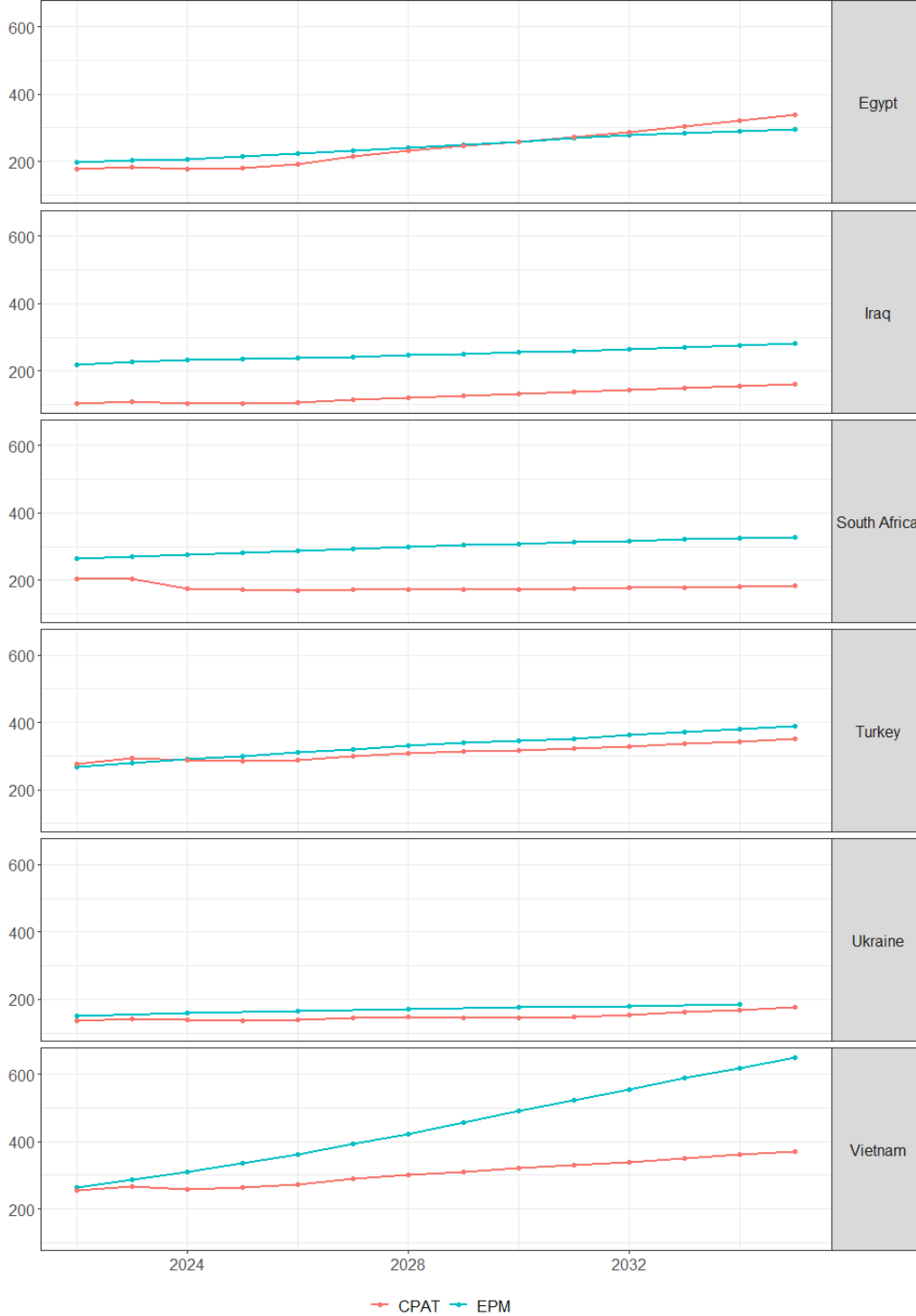
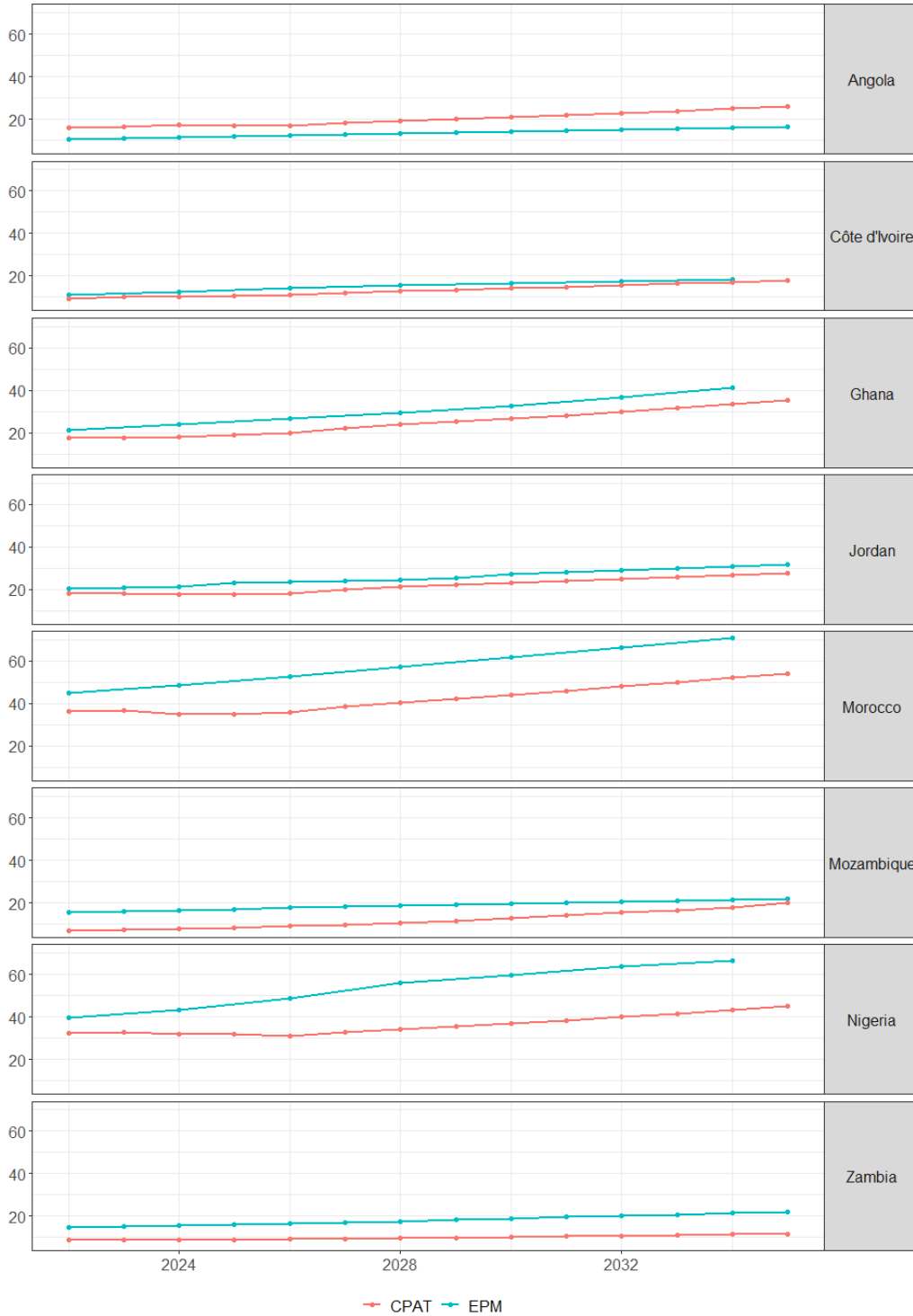


Figure 3.65: Electricity demand in Egypt, Iraq, South Africa, Turkey, Ukraine, and Vietnam

Electricity demand

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), TWh



3.8.3.4.7 Electricity Generation By Fuel Type

3.8.3.4.8 New Investments By Fuel Type

3.8.4 Ex-post studies

3.8.4.1 How effective is the carbon pricing, really? A literature review

Despite voluminous literature on the carbon tax, few empirical works have investigated the effectiveness of a carbon tax and ETS in reducing emissions. Figure 3.70 provides a first attempt to compare the estimates according to three different methods employed in the literature, that is counterfactual scenario and the estimation of semi-elasticity. It is worth noting that this comparison might be imperfect as under a counterfactual scenario some estimates have been annualized based on the policy implementation window, similarly to Green (2021). Moreover, Figure 3.70 reports both short- and long-term estimates.

Two main key findings stand out from ex-post quantitative assessments of carbon pricing policies since 1990.

First, experience with carbon pricing and hence the empirical evidence is primarily from developed and emerging economies. In particular, studies assessing the effectiveness of a carbon tax focus on OECD countries or Northern European countries, which implemented a carbon tax earlier and for which time series data are available. Only few recent studies evaluate ex-post estimates of the effects of carbon tax on CO₂ emissions across the world. At the national level, particular emphasis is placed on British Columbia, Sweden and the United-Kingdom. With respect to the assessment of the ETS, the focus is, not surprisingly, on the EU, China, Germany and the United States.

Second, the estimates for overall emission reductions from carbon pricing are minimal to modest, falling in the range of 0 – 2 percent per annum, with significant variations across sectors, but also across countries (Green (2021)).

Nonetheless, several caveats have to be factored in before drawing conclusion:

- **Carbon prices so far have had low coverage, low prices, or both.** The sample size as well as the time horizon might still be too restricted to accurately examine the effect of a carbon pricing instrument. In this respect, empirical results acknowledge that the effects of taxes on emission reductions largely depend on the comprehensiveness of the instrument design and the level of the carbon tax (see Metcalf (2019a)).
- **The carbon price appears to have a non-linear effect**, indicating that its effect becomes stronger above a certain threshold (Aydin and Esen (2018)). For instance, emissions reductions attributable to the EU ETS during the second phase (2008-2012)

Electricity generation by fuel type

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), TWh

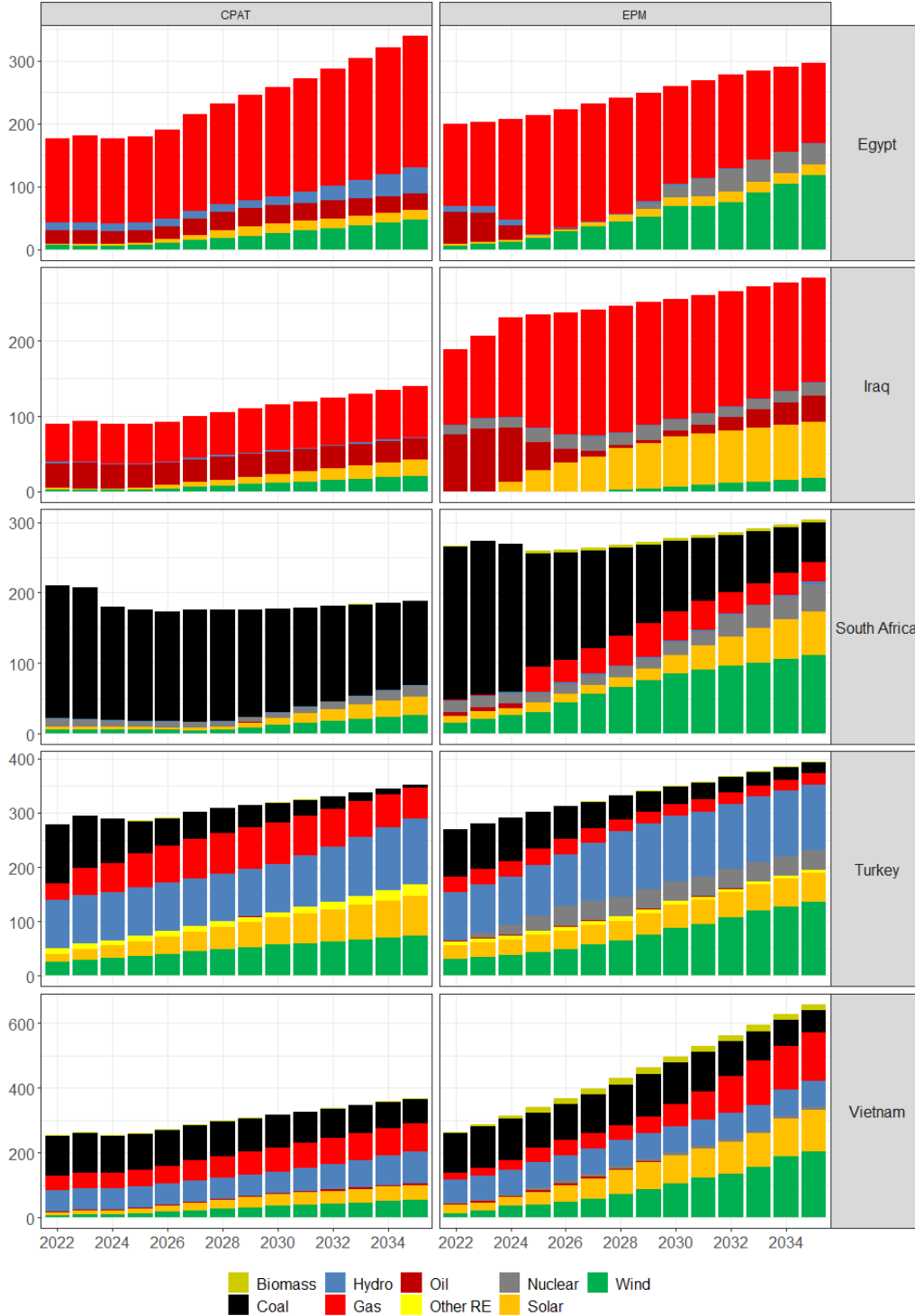


Figure 3.66: Electricity Generation By Fuel Type in Egypt, Iraq, South Africa, Turkey, Vietnam

Electricity generation by fuel type

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), TWh

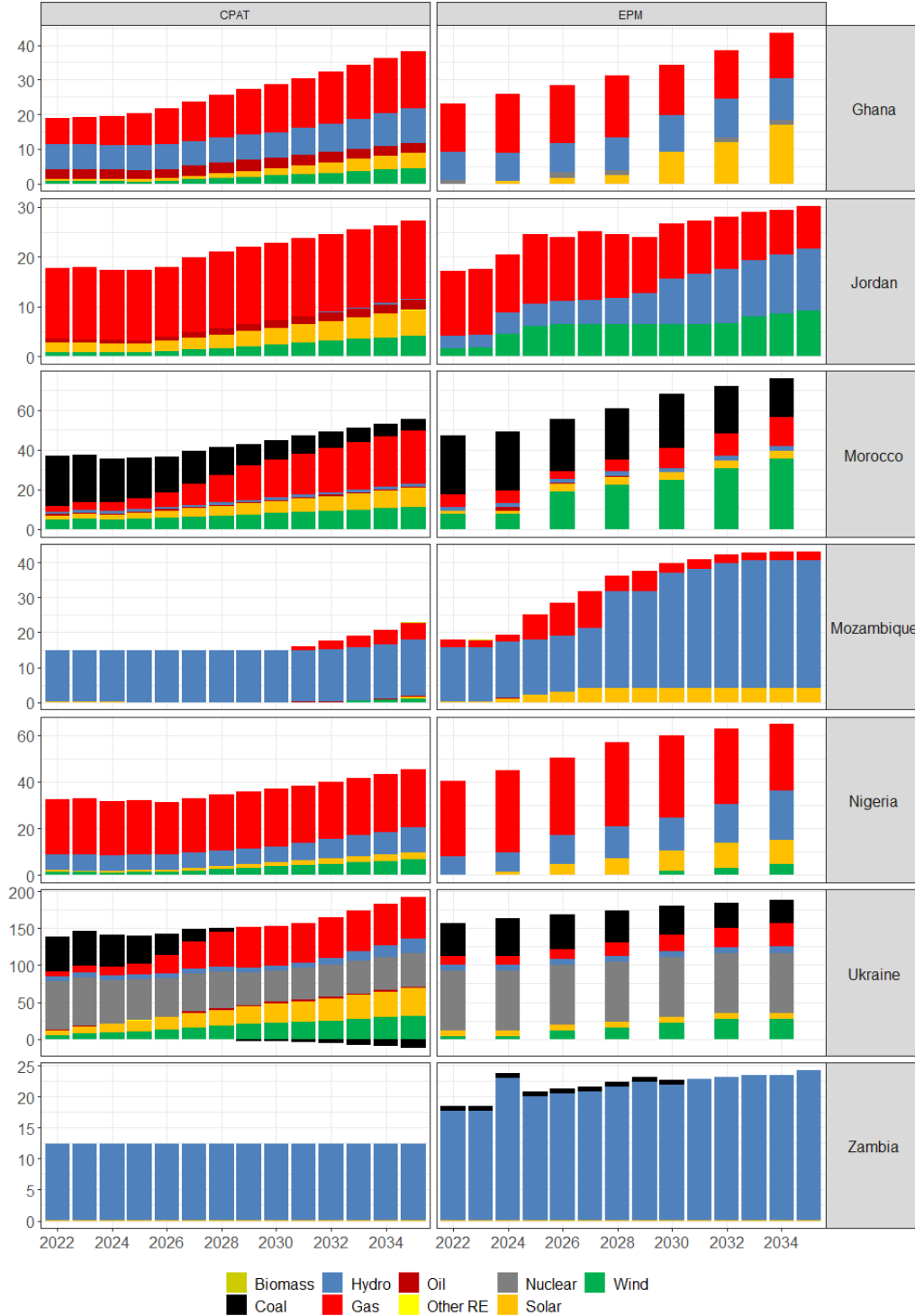


Figure 3.67: Electricity Generation By Fuel Type in Ghana, Jordan, Morocco, Mozambique, Nigeria, Ukraine, Zambia

New investments by fuel type

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), GW

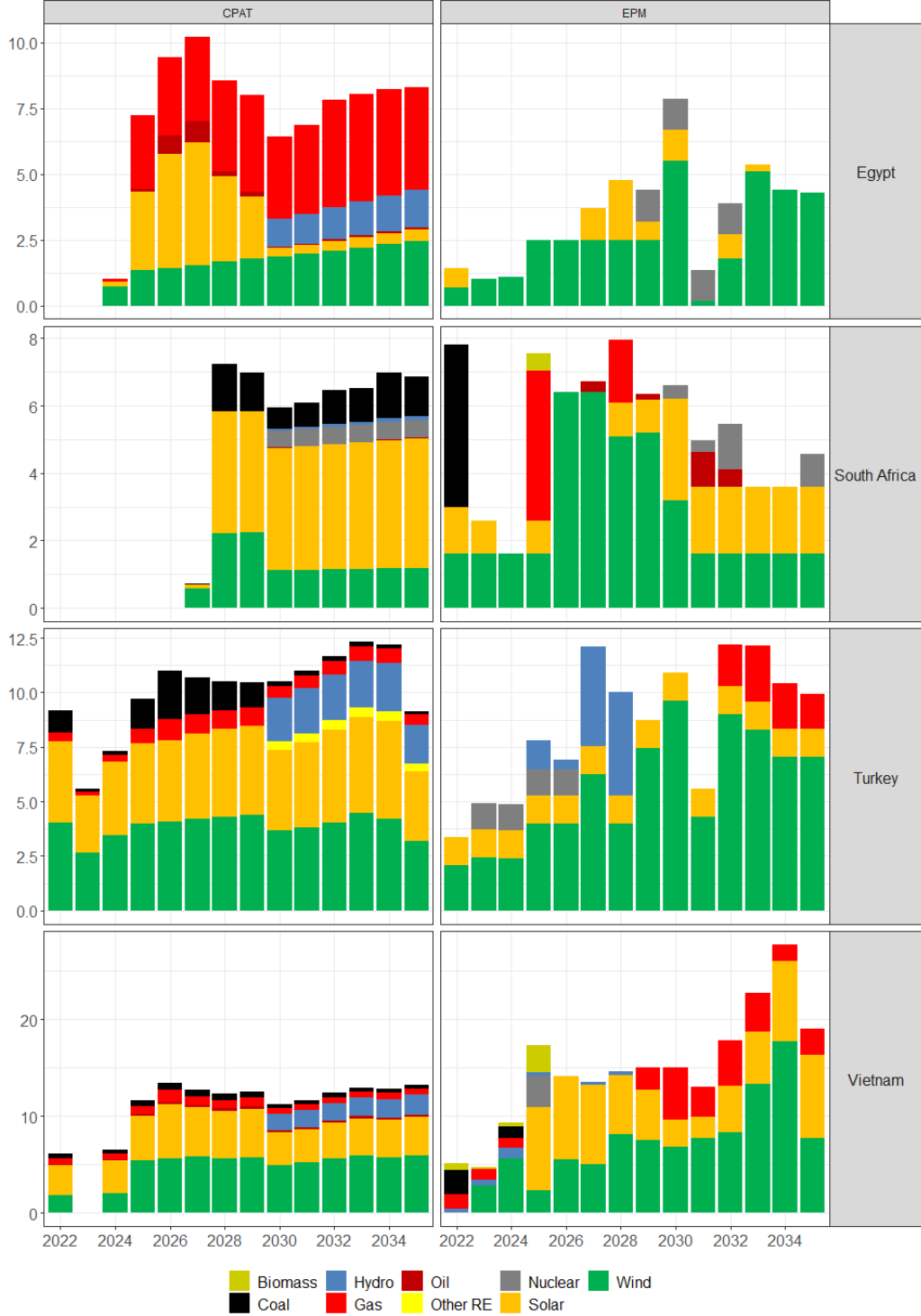


Figure 3.68: New Investments By Fuel Type Egypt, South Africa, Turkey and Vietnam

New investments by fuel type

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), GW

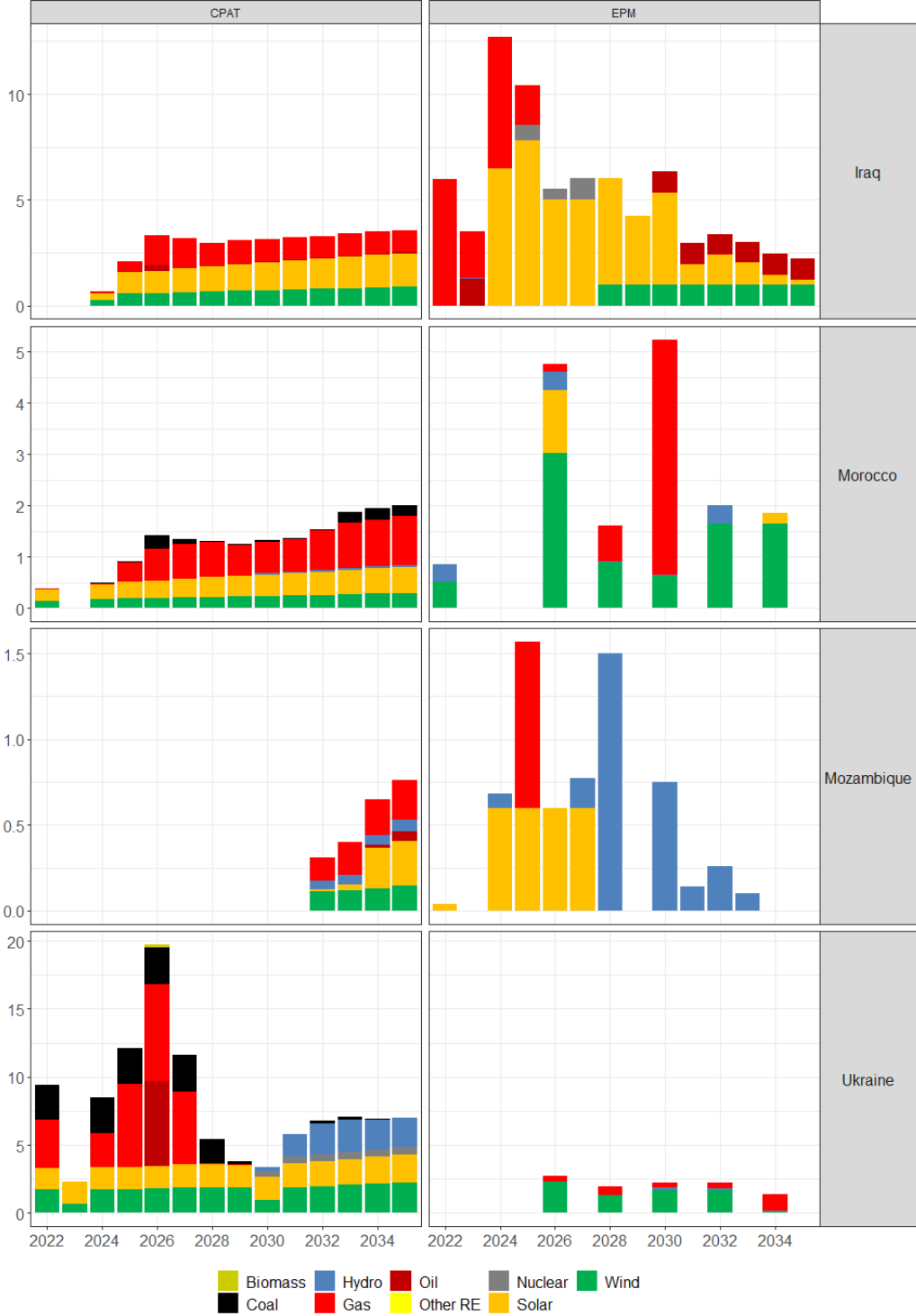


Figure 3.69: New Investments By Fuel Type in Iraq, Morocco, Mozambique, and Ukraine

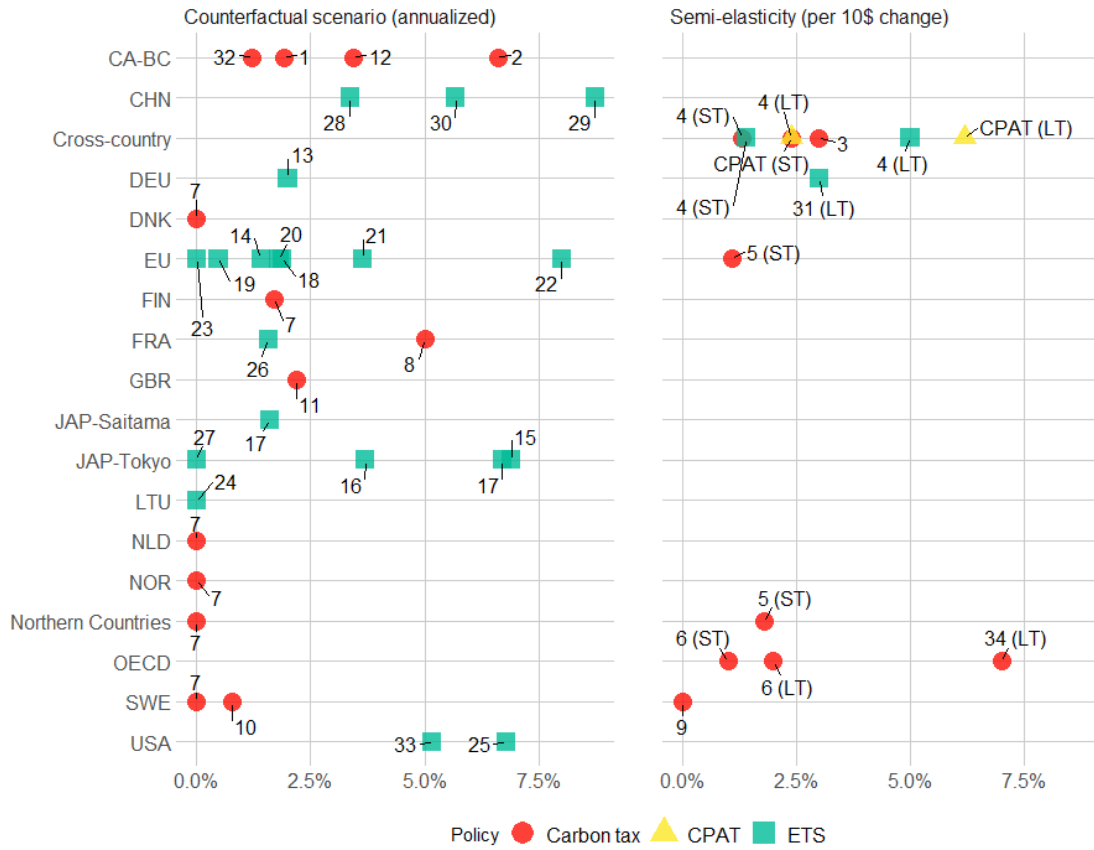
are greater than during the first stage (2005-2007). In the first phase, allowances were freely allocated. In the second phase, the cap was tightened and prices higher.

- **Control variables introduced in empirical studies may poorly capture the effect of the instrument alone.** At the same time, isolating the effect of the carbon pricing instrument from other policies - which are not always considered as environmental policy measures - may lead to insignificant results. However, evaluating a carbon pricing instrument in conjunction with other instruments can lead to effectiveness (see, for example, Shmelev and Speck (2018), who find that a carbon tax is effective when evaluated with a set of policies).
- **The effects of rational ignorance may kick in and eliminate any impact.** Given the transaction costs of investing in low-carbon technologies, agents may not be responsive to a price signal set below a certain threshold.
- **When it comes to the ETS, generalized free allocation can mitigate incentives** (e.g., through the creation of resource rents and barriers to entry). In addition, as more and more emissions are covered by ETSs (such as in China or in the EU) uncertainty on future prices may blunt the responsiveness of agents.

Study estimates are adjusted to derive annual emission reduction effects of the carbon tax and the ETS to make estimates comparable. ST = Short-Term semi-elasticity; LT = Long-term semi-elasticity; CA-BC = British Columbia (Canada). The numbers correspond to the following studies:

1. Rivers, N., & Schaufele, B. (2015). Salience of carbon taxes in the gasoline market. *Journal of Environmental Economics and Management*, 74, 23–36. <https://doi.org/10.1016/j.jeem.2015.07.002>
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**Effects of carbon pricing instruments on average annual emission reductions:
A literature review**



Notes: Numbers correspond to studies presented in the references section. Study estimates are adjusted to derive annual emission reduction effects of the carbon tax and the ETS to make estimates comparable. ST = Short-term semi-elasticity; LT = Long-term semi-elasticity; CA-BC = British Columbia (Canada).

Figure 3.70: Effects of carbon pricing instruments on average annual emission reductions: A literature review

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3.8.4.2 How does CPAT compare to the literature?

In order to compare CPAT's semi-elasticity of CO₂ emissions against the literature, the following settings are used:

- Due to low carbon prices, we employ a low step function, that is **\$10 per ton of CO₂**. Such a step function is comparable to studies estimating semi-elasticities.
- The model is run for all countries for which data are available and factors in the total CO₂ emissions of **171 countries**.

- As CPAT is forward-looking, it covers the period **2019-2035**.
 - As most of studies analyzed their results against a counterfactual scenario, CO2 emission changes in CPAT are compared to the baseline scenario. The estimation of the short- and long- term semi-elasticities is calculated as follows:
 - The total CO2 emissions in ton/CO2 are retrieved from CPAT under the baseline and policy scenarios over the period 2019-2035.
 - Annual changes are thus computed between the baseline and the policy scenarios.
 - **Short-term semi-elasticities** are arbitrarily calculated as an average of the annual changes over the period 2019-2023.
 - **Long-term semi-elasticities** are estimated as an average of the annual changes over the entire period (i.e. from 2019 to 2035).
5. Finally, CPAT holds the advantage to compare CO2 emission changes **across sectors** (i.e. **industry, power, residential and transport**).

The table below (Table 3.33) presents the results. Long-term semi-elasticities are greater than short-term ones, indicating that changes that are not possible in a short period of time are more realistic over a longer time period. When looking into the range of CPAT's estimates across all sectors, results are comparable with those of the literature (see Figure 3.70 above). At the sector level, the power sector records the highest decrease on the long run, which is consistent with Rafaty, Dolphin, and Pretis (2020) ³⁹.

Table 3.33: Short- and long-term semi-elasticities of CO2 emission in CPAT

Sector	Short-term semi-elasticities	Long-term semi-elasticities
All sectors	-2.4%	-6.2%
Industry	-2.7%	-6.2%
Power sector	-2.3%	-8.4%
Residential	-2.2%	-4.9%
Transport	-0.9%	-2.0%

³⁹Rafaty et al. (2020) is comparable to CPAT in the sense that semi-elasticities are assessed globally and across different sectors.

3.8.4.3 References

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3.8.5 Hindcasting

3.8.5.1 Objectives

The hindcasting exercise aims at testing CPAT's forecasts against observed data. It searches to evaluate the performance of the used assumptions when trying to reproduce historical information. In short, the process assumes an historical point in time as its base year, and projects all relevant variables. Key indicators are selected and their projections are compared to real/observed data.

3.8.5.2 Methodology

The current results were obtained using a hindcastable version of CPAT (CPAT 1.0pre_043) with the help of the Multiscenario tool (MT v219). This is an out-of-sample forecasting exercise that simulates data from the year 2000 onward. The analysis uses CPAT methods to forecasts domestic prices, energy consumption and resulting emissions. Observed international prices for the forecasted period were fed as inputs to the simulation.

At the first stage, the focus is set on the forecasts of emissions; in particular, on GHG emissions (excl. LULUCF) and on energy-related CO₂ emissions. The scenarios are run using six countries as test samples:

- Australia (AUS)
- Brazil (BRA)
- China (CHN)
- South Africa (ZAF)
- United Kingdom (GBR)
- United States (USA)

No Policy interventions were modeled, so the results correspond to the ‘Baseline’ output of the model.

The hindcasting exercise relies on an adapted version of CPAT and the MT files, where the first year of calculations is set to an historical point in time. All relevant data tables (e.g. energy consumption and domestic energy prices) are provided for that same base year. The exercise focuses on testing emissions projections, and hence not all features of CPAT are used.

The analysis covers annual data from 2000 to 2017, and assumes that consumption of a fuel in a given sector is a function of sector-specific fuel prices and overall level of economic activity, as measure by the GDP. Default settings and no-policy interventions are used for simulations.

The exercise consists of projecting key modeled variables and comparing those simulations with observed information. The checks are done on a country level basis, with a subset of those being presented here as a sample of results. Results are presented by means of figures, and tables of key statistics, namely the Root Mean Square error (RMSE) and its normalized version.⁴⁰

3.8.5.3 Comparing projected emissions across selected countries

For the selection of countries, CPAT has been able to capture the global trend in emissions. However, there are periods where the volatility of projections is larger than that of observed

⁴⁰The RMSE and its normalized version measure how far the projections are from observed historical data. The RMSE is scale-dependant, while the normalized RMSE is not, allowing for comparison across series or countries. Here, the normalization was done using the averages of the observed series as reference.

data, and where local trends, and in particular levels, are not properly captured. For a fixed set of elasticities, this gaps with respect to observed historical information can result from projected prices showing higher volatility than observed ones. This is explored in a subsequent stage.

3.8.5.3.1 GHG (excl. LULUCF)

CPAT shows a good performance on projecting the trend of emissions in most tested countries. A deeper look at the vertical axis' scale of each plot will show periods of increasing gaps between projected and observed emissions. For a given set of price elasticities of demand, this could be explained by an inverse gap in projected versus observed domestic prices.

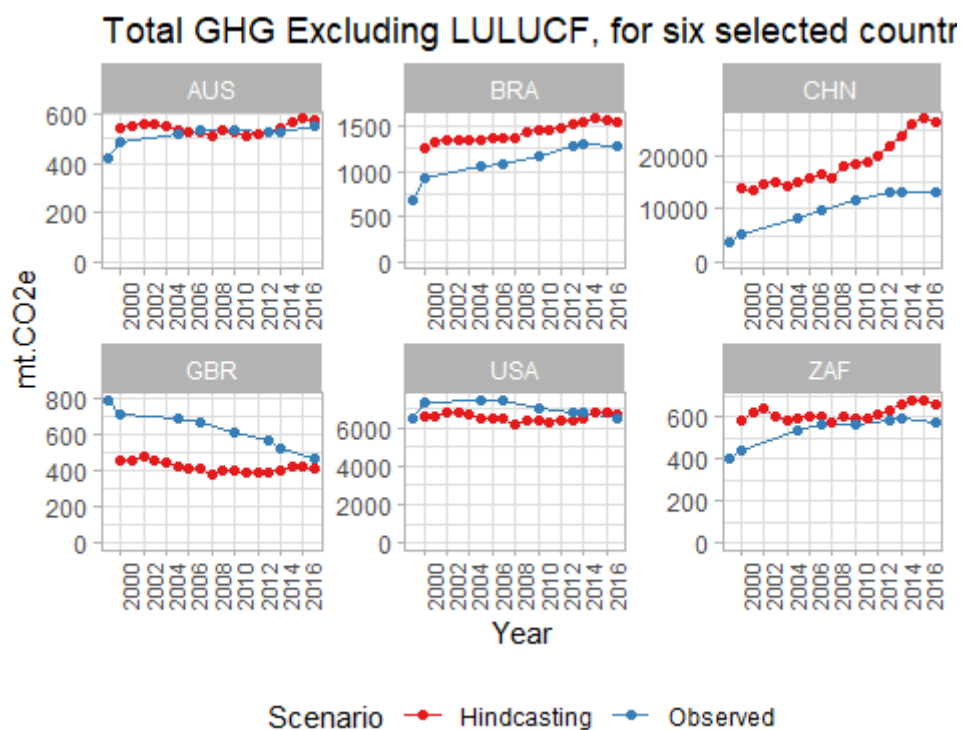


Figure 3.71: Total GHG (mt.CO2e) excluding LULUCF

Table 3.34: RMSE and Normalized RMSE, selected Countries

Country	RMSE	Normalized RMSE
Australia	25.9641	0.0505
Brazil	278.5110	0.2551

Country	RMSE	Normalized RMSE
China	9021.2421	0.9151
United Kingdom	207.1026	0.3285
United States of America	672.3218	0.0966
South Africa	73.7134	0.1383

3.8.5.3.2 CO2 (energy-related)

The previous conclusions extends to the CO2 energy-related emissions. This data, however, should be considered with care as the observed emissions series exclude some years and a linear trend has been assumed to interpolate data for these periods (see for instance, 2007-2014).

Table 3.35: RMSE and Normalized RMSE, selected Countries

Country	RMSE	Normalized RMSE
Australia	35.8338	0.1011
Brazil	127.3467	0.3635
China	8687.0478	1.3373
United Kingdom	155.2571	0.3231
United States of America	637.0707	0.1179
South Africa	85.9752	0.2142

3.8.5.4 A potential source of discrepancies: In-model price forecasts

CPAT is an elasticity-based model where Emissions depend on fossil fuel consumptions, which in turn depend on fuel prices. It follows that, given the negative price elasticity of demand, an over-estimation (under-estimation) of prices with respect to the ones observed in reality, may lead to an under-estimation (over-estimation) of energy consumption, and hence emissions. The case of China, is a clear example of this. Projected prices are below observed historical ones. Since elasticities were computed based on historical prices, this results in higher hindcasted emissions than observed.

It should be noted, however, that the case of the UK escapes this explanation. The hindcasting tool projects lower emissions despite the lower modeled domestic prices. This gap in projected emissions would be amplified if considering in the model the policies that the UK implemented in the mid 2010s. These discrepancies remain for further analysis.

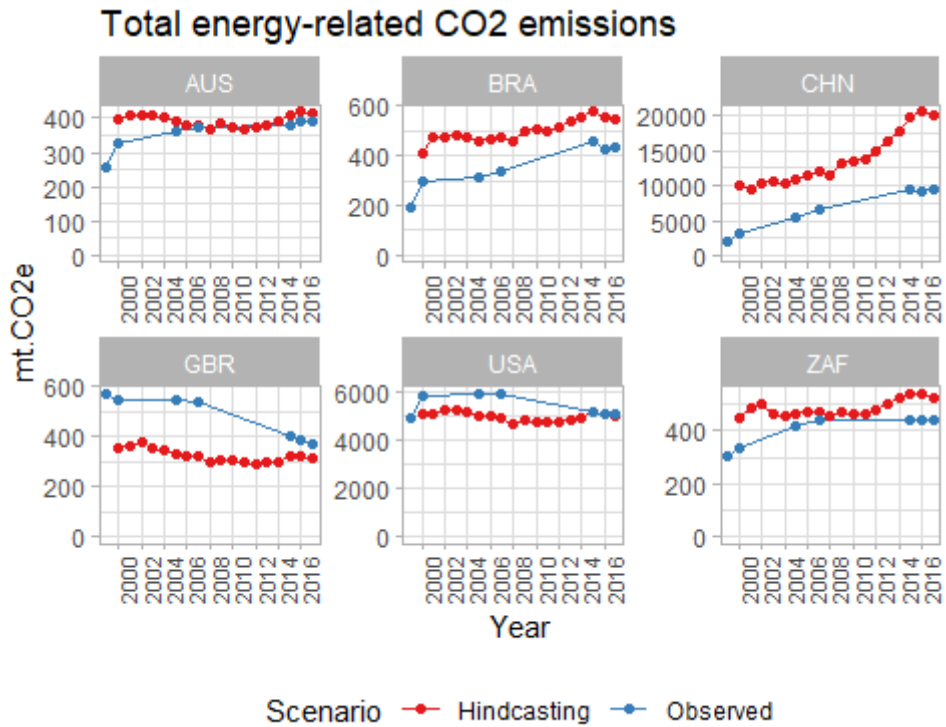


Figure 3.72: Total energy-related CO2 emissions (mt.CO2e)

The tracking of historical information by the simulations may also be improved when setting short and long-term elasticities to model the energy consumption behavior. The current exercise only considers the former, and leaves the latter for further research.

As an additional remark, by construction, CPAT domestic prices for fossil fuels track international market prices for these fuels, and are adjusted with the help of an historical factor. The factor helps tame the volatility. However, for some countries, domestic observed prices remain smoother than projected ones. This may follow as well from policies like existing price regulations, not modeled in the current runs, and also left for further research.

3.8.5.4.1 Coal prices (historical vs CPAT)

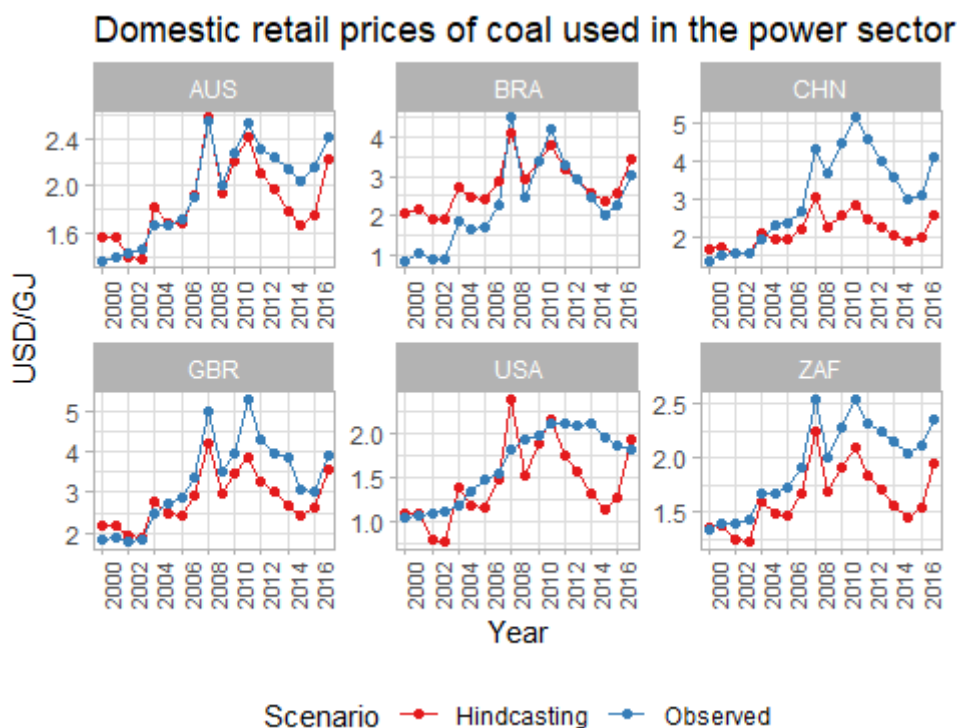


Figure 3.73: Domestic retail prices of coal used in the power sector

Table 3.36: RMSE and Normalized RMSE, selected Countries.

Country	RMSE	Normalized RMSE
Australia	35.8338	0.1011
Brazil	127.3467	0.3635

Country	RMSE	Normalized RMSE
China	8687.0478	1.3373
United Kingdom	155.2571	0.3231
United States of America	637.0707	0.1179
South Africa	85.9752	0.2142

3.8.5.4.2 Coal prices (projected, historical domestic and international)

3.8.5.4.3 All countries

When considering the coal prices used for the power sector in all countries, it can be seen that CPAT forecasts are, on average, above observed prices. The set of figures below, shows this through the distribution of the relative difference (Projections/Observed), and its concentration under the value of “1”.

A subset of years is taken as a reference, but the behavior is consistent for all years. This reinforces the idea that a second set of price elasticities of demand based on price projections may be needed.

3.8.5.5 Conclusions and additional analysis needed

The hindcasting exercise was focused on projecting emissions (GHG and energy-related CO₂). It consists of a partial hindcasting, as the international prices used as inputs correspond to the outturn of prices (observed), instead of projections of prices dating from before the base year selected. It can, hence, serve to better study how the forecasting of domestic prices takes place once the true values of some inputs are known.

For the countries analyzed, CPAT generally shows a good performance capturing the historical trends of the respective variables. In most cases, however, the volatility of observed data is not replicated with CPAT projections. Moreover, depending on the country, CPAT’s projections appear to be persistently under (over) estimating values with respect to historical ones. While this may result from the implementation of policies that were not modeled in the exercise, it can also result from discrepancies in price forecasting, and may be subject to additional country-specific adjustments.

Historical retail prices of coal (domestic and international)

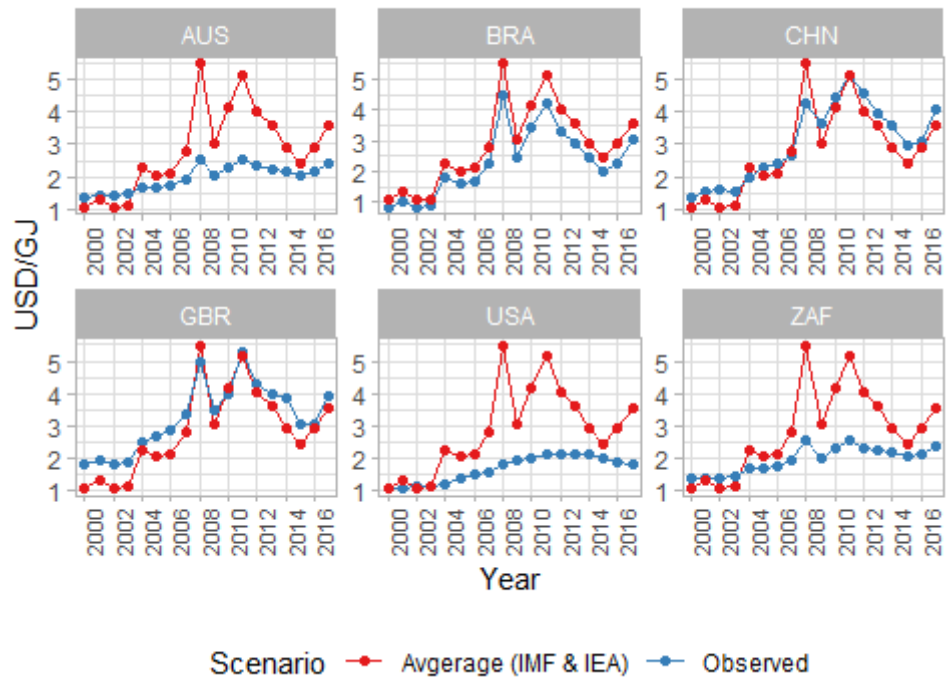


Figure 3.74: Historical retail prices of coal (domestic and international)

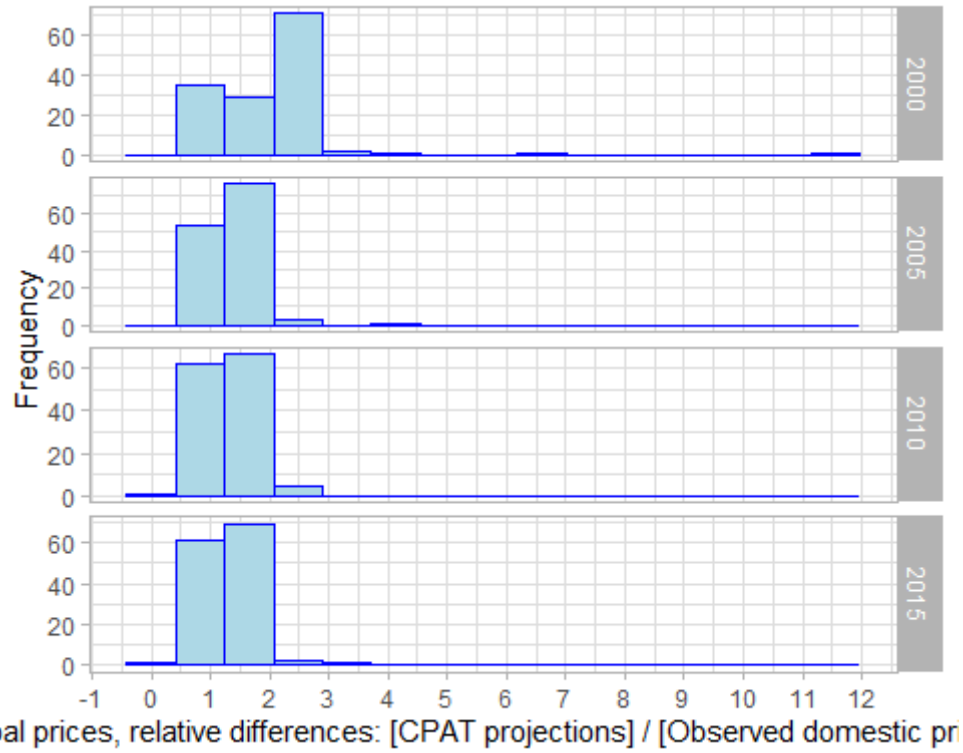


Figure 3.75: Coal prices, relative differences: CPAT projection/Observed domestic prices

3.8.6 Parameter Sensitivity Analysis

3.8.6.1 Objectives

The parameter sensitivity analysis explores the sensitivity of a set of selected parameters with regard to:

- The power sector assumptions;
- Macroeconomic adjustments;
- Elasticity adjustments; and
- Price source adjustments.

The analysis aims to propose a classification of the sensitivity of the parameters, i.e. how CPAT behaves when changing the default parameters, and more especially how the change in parameters affects the emissions' reductions.

3.8.6.2 Methodology

In order to test the sensitivity of the parameters, the following steps were performed:

- **Settings.** Default parameters are used for G20 countries and for a carbon tax increasing from 10\$ to 75\$.
- **Model run.** The MT is run using the same defaults but changing one parameter only.
- **Data.** The database is then compiled, retaining CPAT's output on emissions for G20 countries.
- **Computation.**
 1. Change in Emissions: Carbon Tax \$75 in 2030 vs Baseline
 2. Relative change (i.e. to the default parameter) in percentage points (pp). The difference between the change of CO2 emissions recorded under the default setting and the change in CO2 emissions under the other options is computed in order to analyse how each option is sensitive to the baseline parameter.
- **Output.** Create a sensitivity classification of parameters affecting CPAT's behavior (no sensitivity/negligible/sensitivity/high sensitivity).

3.8.6.3 Results

Based on the methodology described above, the sensitivity of the parameters to CPAT to CO2 emissions varies from **no effect to very sensitive** when focusing on the relative changes (i.e. CO2 emissions reduction relative to the default parameter). The following rule-of-thumb is used to classify the sensitivity of the parameters:

- No effect: no variation
- Negligible: less than 2 percentage points
- Sensitivity: between 2 and 5 percentage points
- High sensitivity: more than 5 percentage points

The table below summarizes the results of the sensitivity analysis.

Table 3.37: CPAT's parameters sensitivity results

Parameter	Assumption	Description	Change in Emissions: Carbon Tax \$75 in 2030 vs Base-line	Relative change (i.e. to the default parameter) in percentage points (pp)	Sensitivity
Power model	Average	Average between the elasticity and engineer models. The two models differ in their assumptions on generation cost so that even though they share a power demand framework, they can differ in modeled power demand despite the equations being the same.	- 29%	-	-

Parameter	Assumption	Description	Change in Emissions: Carbon Tax \$75 in 2030 vs Base-line	Relative change (i.e. to the default parameter) in percentage points (pp)	Sensitivity
	Elasticity	The 'elasticity' model is the original IMF power sector model explained in IMF board paper (2019)	- 34%	5% more sensitive	High
	Engineering	The power demand model in the engineering model is based on specific sectors, and the elasticity model is more aggregated.	- 22%	7% less sensitive	High
K parameter	k = 2*	The k parameter determines the speed of transitioning between generation types with a different cost. K is a measure of local cost variability and other reasons (such as load matching) for higher cost choices still being included in the generation mix.	- 29%	-	Negligible
	k = 6		- 29%	0	Negligible

Parameter	Assumption	Description	Change in Emissions: Carbon Tax \$75 in 2030 vs Base-line	Relative change (i.e. to the default parameter) in percentage points (pp)	Sensitivity
	k		-	0	Negligible
	=		29%		
	10				
		2*Maximum historical rate or 4%			
Renewable growth rate	Very high	Very of capacity, whichever is higher	-	3%	Medium
	High	Maximum historical rate	-	32% more sensitive	
	High	Maximum historical rate	-	1% more sensitive	Negligible
	High	Maximum historical rate	30%		
	Medium	Halfway between maximum and average historical rate.	-	-	-
	Medium	Average historical rate	29%		
	Low	Average historical rate	-	0	Negligible
	Low	Average historical rate	29%		

Parameter	Assumption	Description	Change in Emissions: Carbon Tax \$75 in 2030 vs Base-line	Relative change (i.e. to the default parameter) in percentage points (pp)	Sensitivity
Fiscal multipliers adjustment		Increase all fiscal multipliers by 1 High standard deviation	- 29%	0	No effect
		No adjustment Medium*	- 29%	-	-
		Decrease all fiscal multipliers by 1 Low standard deviation	- 29%	0	No effect
GDP growth adjustment		Increase forecast GDP growth by High 50%	- 30%	1% more sensitive	Negligible
		No adjustment Medium*	- 29%	-	-

Parameter	Assumption	Description	Change in Emissions: Carbon Tax \$75 in 2030 vs Base-line	Relative change (i.e. to the default parameter) in percentage points (pp)	Sensitivity
	Low	Reduce forecast GDP growth by 50%	- 29%	0	Negligible
International energy prices forecast	Average*	Average of above four sources	- 29%	-	-
	IMF-IEA	Average of IEA and IMF	- 28%	1% less sensitive	Negligible
	EIA	Institutions' forecasts for international prices for oil, gas, and coal	- 32%	3% more sensitive	Medium

Parameter	Assumption	Description	Change in Emissions: Carbon Tax \$75 in 2030 vs Base-line	Relative change (i.e. to the default parameter) in percentage points (pp)	Sensitivity
	IEA		- 28%	1% less sensitive	Negligible
	IMF		- 28%	1% less sensitive	Negligible
	WB		- 30%	1% more sensitive	Negligible
International energy prices adjustment	High	Increase forecast prices by 50%	- 20%	9% more sensitive	High

Parameter	Assumption	Description	Change in Emissions: Carbon Tax \$75 in 2030 vs Base-line	Relative change (i.e. to the default parameter) in percentage points (pp)	Sensitivity
		No adjustment	-	-	
	Medium*		29%		-
	Low	Reduce forecast prices by 50%	- 31%	2% less sen- si- tive	Medium
Adjust in- come elas- tic- i- ties for GDP level	Yes*	Adjusts income elasticities for electricity, gasoline and diesel with GDP levels (elasticities decrease as countries increase their per capita GDP). The intuition is that, for example, in middle-income countries households purchase fridges, but do not purchase additional fridges as their income increase further.	- 29%	-	-
	No		- 30%	1% more sen- si- tive	Negligible

Parameter	Assumption	Description	Change in Emissions: Carbon Tax \$75 in 2030 vs Base-line	Relative change (i.e. to the default parameter) in percentage points (pp)	Sensitivity
Income elasticities adjustment		Increase by 2 standard deviations	- 29%	0	Negligible
	Very high	Increase by 1 standard deviation	- 29%	0	Negligible
	High	No adjustment	- 29%	0	Negligible
	Medium*	Reduce by 1 standard deviations	- 29%	0	Negligible
	Low	Reduce by 2 standard deviations	- 29%	0	Negligible
Very low			- 29%	0	Negligible

Parameter	Assumption	Description	Change in Emissions: Carbon Tax \$75 in 2030 vs Base-line	Relative change (i.e. to the default parameter) in percentage points (pp)	Sensitivity
Prices elasticities adjustment		Increase by 2 standard deviations	-	10%	High
	Very high		39%	more sensitive	
		Increase by 1 standard deviation	-	6%	High
	High		35%	more sensitive	
	No adjustment		-	-	-
	Medium*		29%		
		Reduce by 1 standard deviations	-	9%	High
Low			20%	less sensitive	

Parameter	Assumption	Description	Change in Emissions: Carbon Tax \$75 in 2030 vs Base-line	Relative change (i.e. to the default parameter) in percentage points (pp)	Sensitivity
		Reduce by 2 standard deviations			
	Very low		-	22%	High
	low		7%	less sensitive	
	*	De- notes the de- fault pa- ram- e- ter			

3.9 Appendices

3.9.1 Appendix A - Macro data of CPAT: Sources and codes

This table shows the sources for all macro data in CPAT.

Indicator	Variable	Unit	Source
NGDP_D	GDP Deflator	Index	WEO
	Discount index - 2021	Index	
NGDP_RPCH	GDP growth - nominal (current prices, LCU)	% change	WEO
	GDP growth - real (constant prices)	% change	WEO
NGDP_R	GDP - real (constant prices)	LCU bn	WEO
	GDP - real (current prices)	USD bn	WEO
NGDP	GDP - real (constant prices) - 2021 USD	USD bn	WEO
	GDP - nominal (current prices)	LCU bn	WEO
NGDPRPC	GDP per capita - real (constant prices)	LCU	WEO
	GDP per capita - real (constant prices)	PPP; 2011 international dollar mm	WEO
LP	Population		GBD, WEO, WDI
	Population	% change	GBD, WEO, WDI
LE	Employment	mm	WEO
	Exchange rate	LCU/USD	WEO
ENDA	Euro exchange rate	EUR per US\$	WEO
	GDP growth - real (constant prices)	% change	WEO
SP.URB.GROW	Urban population growth - latest available	% change	WDI
	Urban population growth (annual %)	% change	WDI
NGDP_D	GDP Deflator (2012=100)	index	WEO

Indicator	Variable	Unit	Source
PCPI_PCH	CPI Change	%	WEO
	Inflation index	%	
pcpi	GDP growth - real	% change	WEO
gdgg.base.pct	(constant prices)		IMF
	Baseline GDP - real	LCU bn	WEO
gdpl.base.lcu	(constant prices) - LCU		IMF
	Baseline GDP - real	USD bn	WEO
gdpl.base.usd	(constant prices) - USD		IMF
	bn		WEO
	Baseline ln(GDP per capita)		IMF
			WEO
	Deflator- 2021 - used hereafter - World		IMF
			WEO

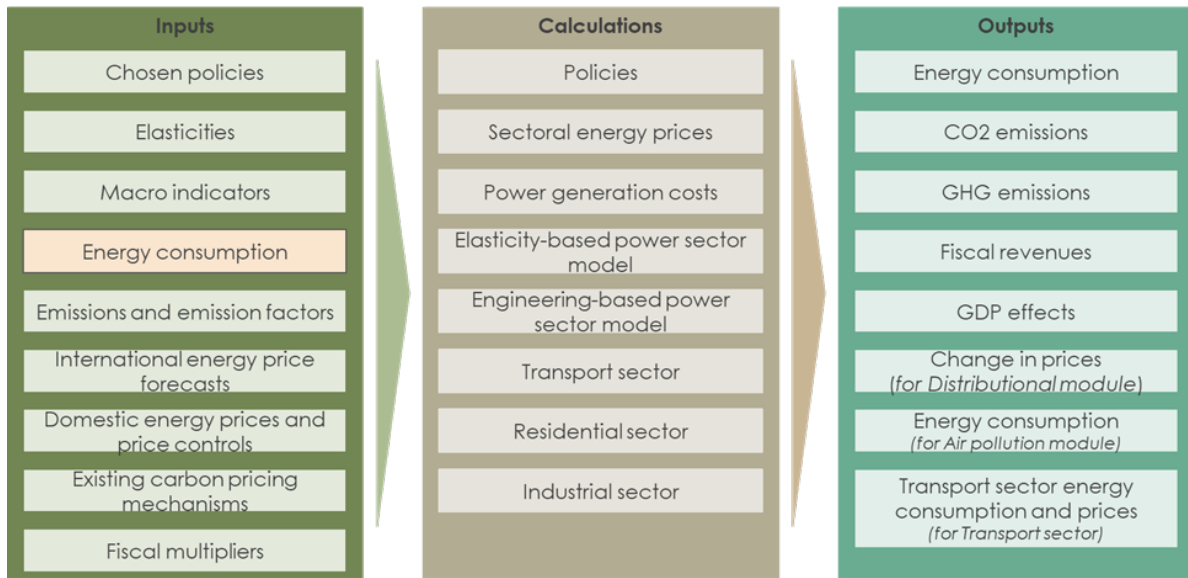
3.9.2 Appendix B - Energy balances

Energy balances are a key source of information for CPAT. While the model uses energy consumption as a main input for the mitigation module, energy consumption is itself built based on the structure and information provided in the energy balances framework. This document presents the main principles used to transform the energy balances information into a structure consistent with CPAT's fuels and sectors, as well as the steps taken to build energy consumption tables based on the CPAT energy balances.

We use the IEA Extended World Energy Balances, and Enerdata Energy Balances as the main sources to build the energy consumption tables used in CPAT.

3.9.2.1 CPAT fuels

The main energy products in CPAT are presented in the table below.



Covered in this document

Figure 3.76: Mitigation module overview

CPAT energy products	Corresponding IEA energy products codes	Corresponding IEA energy products
Coal	HARDCOAL BROWN, BKB	Hard coal
	ANTCOAL	Brown coal, Brown coal briquettes
	COKCOAL, OVEN- COKE, GAS- COKE, COKEOVGS	Anthracite
	BITCOAL, SUB- COAL LIGNITE	Coking coal, Coke oven coke, Gas coke, Coke oven gas
		Other bituminous coal, Sub-bituminous coal
		Lignite

CPAT en- ergy prod- ucts	Corresponding IEA energy products codes	Corresponding IEA energy products
	PEAT, PEAT- PROD	Peat, Peat products
	BLFURGS, GASWKSGS, OGASES	Blast furnace gas, Gas works gas, Other recovered gases
	COALTAR, PATFUEL NATGAS	Coal tar, Patent fuel
Natural gas		Natural gas
	NGL	Natural gas liquids
Gasoline	NONBIOGASO	Motor gasoline excl. biofuels
Diesel	NONBIODIES	Gas/diesel oil excl. biofuels
LPG	LPG	Liquefied petroleum gases
Kerosene	OTHKERO	Other kerosene (other than kerosene used for aircraft transport) Kerosene type jet fuel excl. biofuels
Jet fuel	NONBIOJETK	
	AVGAS JETGAS	Aviation gasoline Gasoline type jet fuel
Other oil prod- ucts	CRUDEOIL; CRNGFEED	Crude oil; Crude/NGL/feedstocks (if not details)
	RESFUEL	Fuel oil
	OILSHALE, BITU- MEN, PET- COKE	Oil shale and oil sands, Bitumen, Petroleum coke

CPAT en- ergy prod- ucts	Corresponding IEA energy products codes	Corresponding IEA energy products
	ETHANE	Ethane
	LUBRIC, NAPH- THA, PARWAX, WHITESP, ADDI- TIVE	Lubricants, Naphtha, Paraffin waxes, White spirit & industrial spirit (SBP), Additives/blending components
	REFFEEDS, REFIN- GAS	Refinery feedstocks, Refinery gas
	NONCRUDE, ONON- SPEC	Other hydrocarbons, Other oil products
Biomass	PRIMSBIO	Primary solid biofuels
	CHARCOAL	Charcoal
	BIOGASOL	Biogasoline
	BIODIESEL	Biodiesels
	OBIOLIQ	Other liquid biofuels
Wind	WIND	Wind energy
Solar	SOLARPV	Solar photovoltaics
	SOLARTH	Solar thermal
Hydro	HYDRO	Hydro energy
Other re- new- ables	BIOJETKERO; BIO- GASES	Bio jet kerosene; Biogases
	GEOTHERM	Geothermal

CPAT en- ergy prod- ucts	Corresponding IEA energy products codes	Corresponding IEA energy products
	INDWASTE; MUNWASTEN; MUNWASTER TIDE	Industrial waste; Municipal waste (non-renewable); Municipal waste (renewable)
	RENEWNS	Tide, wave and ocean Non-specified primary biofuels and waste Nuclear energy
Nuclear	NUCLEAR ELECTR	Electricity
Electricity		

The table below provides indications on the code names used in CPAT.

Fuel code	Energy use by fuel and sector
bio	Biomass
bgs	- in which: biodiesel
bdi	- in which: biogasoline
obf	- in which: other liquid biofuels
coa	Coal
die	Diesel
ecy	Electricity
gso	Gasoline
hyd	Hydro
jfu	Jet fuel
ker	Kerosene
lpg	LPG
nga	Natural gas
nuc	Nuclear
oop	Other oil products
ore	Other renewables / Total self-generated renewables
ren	Renewables
sol	Solar
wnd	Wind

Starting from CPAT Prototype version 1.478, we separate biomass to biogasoline, biodiesel

and other biofuels.

3.9.2.2 CPAT energy sectors

The energy sectors in CPAT are based on the IEA Extended Energy Balances dataset. We divide all energy flows into three main categories:

- Raw energy supply,
- Energy transformation, and
- Final energy consumption.

For each country j , the balancing flow in raw energy supply category is Total Primary Energy Supply (TPES), which should be equal to the sum of Imports, Production, Exports (negative), Stock changes, International marine bunkers (only on the world level) and International aviation bunkers (only on the world level). Stock changes and bunkers were combined in “Stock and bunker changes (STOCKCHA)” flow.

$$TPES_j = Production_j + Imports_j - Exports_j + STOCKCHA_j$$

Energy transformation category includes the following IEA flows: transformation processes (TOTTRANF, includes electricity generation), transfers (TRANSFER), energy industry own use (OWNUSE), distributional losses (DISTLOSS), and statistical differences (STATDIFF). The balancing equation for total final consumption (TFC) is:

$$TFC_j = TPES_j + TOTTRANF_j + TRANSFER_j + OWNUSE_j + DISTLOSS_j + STATDIFF_j$$

In transformation processes, we separate the power sector - transformation of fuels into electricity. We include main activity producer electricity plants, autoproducer electricity plants, main activity producer CHP plants, and autoproducer CHP plants. The main sector groups in final energy consumption are:

- Industry
- Transport
- Building
- Power sector

We disaggregate transport and industry further to sectors.

3.9.2.3 CPAT fuels and sectors overlap

The fuels and sectors specified above form an energy balances table in the mitigation module, which shows the amount of fuels consumed by each subsector in industry, transport, residential or other sector for energy purposes, and the amount of fuels consumed in the power sector to generate electricity (see the screenshot).

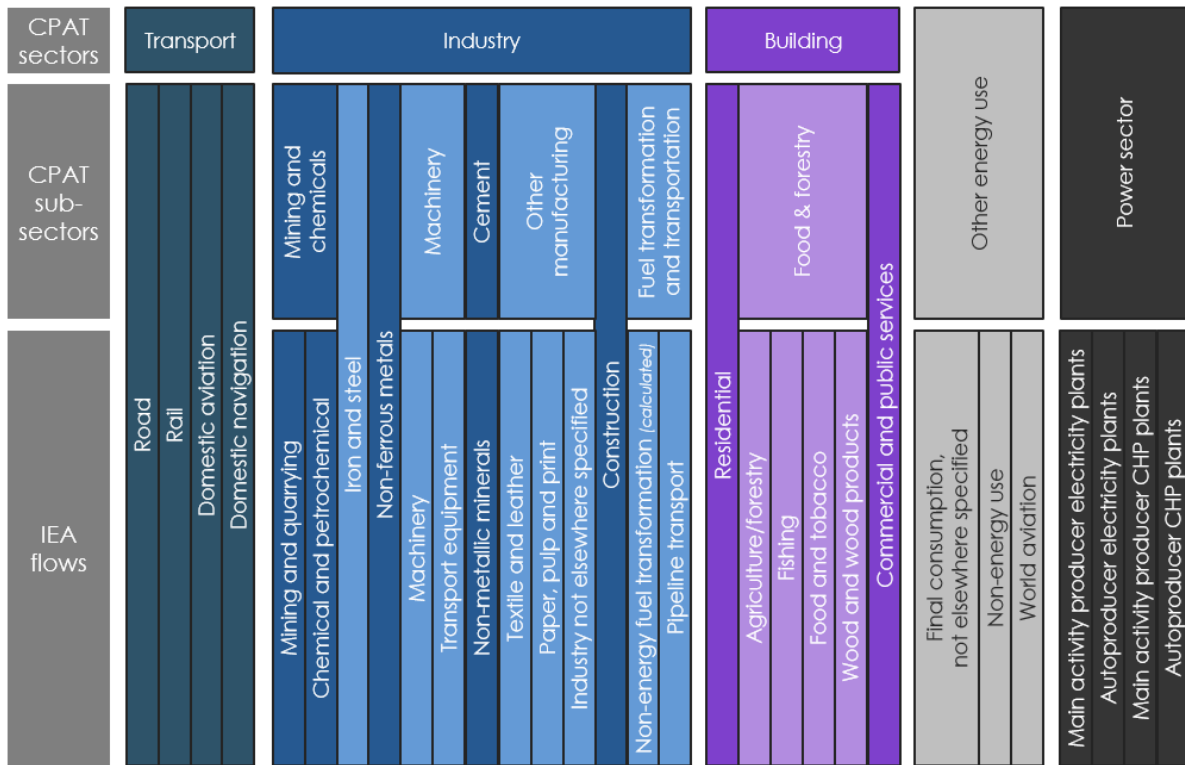


Figure 3.77: Sectors disaggregation in CPAT

Energy Balances – TPES and TFC (ktoe, unless otherwise specified)
Example table

2019 IEA Code CPAT code		ENERGY FLOWS														Power		Additional Information			
		Raw energy supply					Energy transformation									ELECTRICITY OUTPUT	AGRICULTURE	FISHING	FOOD	WOOD	
		IMPORTS	PRODUCTION	EXPORTS	STOCKCHG	TES	STATOFF	TRANSFER	OWNUSE	DISTLOSS	TOTTRANSF	POWER	TFC	ELCOUTPUT	IND_AGRIC						IND_FISH
Imports	Production	Exports	Stock and bunker changes	Primary Energy Supply (TPES)	Statistical diff	Transfers	Energy industry own use	Distribution losses	Total transformation process...	... of which for power	Total Final Energy Consumption (TFC)	Electricty output (TWh)	agriculture and forestry	Fishing	Food production	Wood production					
ecp	Electricity	341	0	-22	0	319	-	0	0	-286	-1,724	11,364	10,303	-	0	76	0	1,062	42		
coa	Coal	543,448	62	-36	153	722	-	-22	0	0	-333	11,364	366	-	1,280	0	0	0	0		
nga	Natural gas	5,630	41,524	-231	18	47,009	-	0	-4,267	-5,130	-2,421	-14,366	-14,366	20,234	-	91,004	0	0	1,484	8	
oop	Other oil products	368	26,671	-5,477	18	21,581	-	572	2,577	-1,628	0	-18,493	-397	3,603	-	1,443	101	0	0	0	
gso	Gasoline	391	0	0	23	421	-	0	0	0	0	5,756	0	6,176	-	0	0	0	0	0	
die	Diesel	1393	0	-23	78	2,168	-	0	0	-5	0	6,155	-417	10,176	-	1,598	3,256	0	0	0	
ker	Kerosene	0	0	0	0	0	-	1	0	0	0	8	0	9	-	0	0	0	0	0	
lpg	LPG	0	0	-1,346	-7	-1,353	-	0	2,195	-37	0	851	0	1,655	-	0	83	0	0	0	
ifu	Jet fuel	232	0	-2	-1,130	-901	-	-17	0	0	0	1,540	0	622	-	0	0	0	0	0	
wind	Wind	0	430	0	0	430	-	0	0	0	0	-430	-430	0	-	4,597	0	0	0	0	
sol	Solar	0	69	0	0	69	-	0	0	0	0	-69	-69	0	-	800	0	0	0	0	
hyd	Hydro	0	2,365	0	0	2,365	-	0	0	0	0	-2,365	-2,365	0	-	27,510	0	0	0	0	
ore	Other renewables	0	73	0	0	73	-	0	0	0	0	-73	-73	0	-	258	0	0	0	0	
nuc	Nuclear	0	2,209	0	0	2,209	-	0	0	0	0	-2,209	-2,209	0	-	8,478	0	0	0	0	
bio	Biomass	0	4,775	-903	0	3,872	-	-1	0	0	0	-902	-744	2,363	-	1,334	0	0	0	0	
bgs	- in which biogasoline	0	544	0	0	544	-	-5	0	0	0	0	0	539	-	0	0	0	0	0	
bdf	- in which biodiesel	0	1,391	-303	0	1,088	-	4	0	0	0	0	0	1,012	-	0	0	0	0	0	
oil	- in which other liquid fuels	0	0	0	0	0	-	0	0	0	0	0	0	0	-	0	0	0	0	0	
hea	Heat	0	0	0	0	0	-	0	0	0	0	0	0	0	-	0	0	0	0	0	
	Total	10,151	78,179	-8,047	-840	79,442	0	533	504	-7,087	-4,215	-12,564	-10,003	56,614	-	139,146	3,516	0	2,546	50	

Figure 3.78: Figure 78: Energy Balances

Figure 3-48: Energy Balances

As the energy balances and prices are the main inputs for the Mitigation module, it is also essential to understand the overlap between energy prices and energy consumption by sector and fuels. The table below depicts the energy consumption table obtained in CPAT following transformations from international sources and CPAT’s own projections. For fossil fuels and electricity we have sector-specific or general energy prices and taxes per energy unit (please see a separate documentation on CPAT Prices and Taxes), for renewables we use price indices instead.

Figure 3-49 explains the overlap of CPAT energy prices and sectors.

Fuel prices	Gasoline															
	Diesel															
	LPG															
			Coal		Coal		Coal									
			Natural gas				Nat. gas									
			Electricity				Electricity		Nat. gas							
			Oil products*													
		Biomass*														
		Kerosene*														
CPAT sectors	Transport		Industry				Building		Power							
CPAT subsectors	Road	Rail	Domestic aviation	Domestic navigation	Mining and chemicals	Iron and steel	Non-ferrous metals	Machinery	Cement	Other manufacturing	Construction	Fuel transformation and transportation	Residential	Services (public & private)	Food & forestry	Power sector

Figure 3.79: Figure 79: CPAT energy prices and sectors overlap

Figure 3-49: CPAT energy prices and sectors overlap

3.9.2.4 Energy Consumption (EC) construction for CPAT

The purpose of this section is to present the sequence of processes applied to build and project Energy Consumption data in CPAT format, that is also sufficiently derived from original international sources. This process is applied as well to build a set of time series of Energy Consumption used for regression analysis and hindcasting.

Raw Inputs:

- Energy Balances (EB) from IEA (yearly information. 2018 and 2019)
- Energy Balances (EB) from Enerdata (yearly information. Last update:

2018)

Intermediate inputs:

- CPAT projected Energy Consumption (EC) (2019)
- User defined parameters for projections and for EC adjustment

Outcome:

Energy Consumption tables created using CPAT own structure, assumptions and projections based on raw data published by international databases. The table below depicts an example structure of such table:

Fuel Code	SECTOR -> CPAT code -> Energy use by fuel and sector	POWER		TRANSPORT		DOMESTIC AVIATION & SHIPPING		BUILDINGS			INDUSTRY (excl. foo and srv)										OTHER			Total energy use territorial consumption	Share of final consumption	Total non-renewables energy and non-territorial consumption				
		elec	pow	road	rail	avi	nav	res	foo	srv	mch	ltn	ntm	mac	cem	omn	constr	ft	oen	Other energy use	Other non-energy use	World aviation								
		Electricity output (GWh)	Energy used in power generation	Road	Rail	Domestic aviation	Domestic shipping	Residential	Food & forestry	Services (public & private)	Mining & Chemicals	Iron and steel	Other metals	Machinery	Cement	Other manufact. veg	Construction	Fuel transformation & transgenera-tion												
ele	Electricity	0	-11,964	0	45	0	0	3,713	1,180	2,678	1,039	509	425	216	399	599	0	2,080	0	0	0	0	0	0	0	0	12,883	17%	0	
coa	Coal	1,260	397	0	0	0	0	0	0	0	287	0	0	0	45	0	48	0	39	0	0	0	0	0	0	0	686	1%	36	
nga	Natural gas	91,004	14,555	2,043	0	0	0	8,474	1,452	12,026	462	803	213	55	11,120	2,900	0	0	683	0	0	0	0	0	0	0	33,734	46%	683	
oap	Other oil products	1,449	397	0	0	0	72	0	101	52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10,537	14%	2,901		
gso	Gasoline	0	0	6,176	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6,176	8%	0		
dse	Diesel	1,998	417	6,478	0	0	238	0	3,256	102	0	0	0	0	102	0	0	0	0	0	0	0	0	0	0	0	10,593	14%	0	
ker	Kerosene	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0%	0		
lpg	LPG	0	0	0	0	0	0	1,192	83	199	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	66	0%	0		
ifu	Jet fuel	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	66	0%	0		
wnd	Wind	4,897	430	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	430	1%	0		
sol	Solar	800	69	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	69	0%	0		
hyd	Hydro	27,510	2,365	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,365	3%	0		
ore	Other renewables	156	73	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	73	0%	0		
nuc	Nuclear	8,478	2,209	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,209	3%	0		
bio	Biomass	1,394	744	1,550	0	0	0	252	0	153	0	0	0	0	0	1,013	0	159	0	0	0	0	0	0	0	0	3,872	5%	0	
bgs	- in which: biogasoline	0	0	539	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	544	1%	0	
bdl	- in which: biodiesel	0	0	1,012	0	0	0	0	0	0	0	0	0	0	0	0	0	-4	0	0	0	0	0	0	0	0	1,008	1%	0	
obf	- in which: other liquid biofuels	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%	0
heat	Heat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0%	0
ren	Total self-generated renewables (nonbiomass)	5,146	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
total		77,249	139,146	21,968	16,249	0	622	310	9,927	4,932	1,714	462	1,090	218	56	1,120	4,651	0	10,745	0	3,686	0	0	0	0	0	74,063	100%	3,686	

Figure 3.80: Figure 80: Energy Consumption

Figure 3-50: Energy Consumption

The CPAT energy consumption projections for the base year include a sub-process under which the fuel transformation sector is created. In CPAT we transform balances into final energy consumption (buildings, industry, transport, other), power sector (part of energy transformation in balances) and fuel transformation. Fuel Transformation sector is determined by the difference between primary and final energy consumption, subtracting Fuel Transformation in the power sector. Additionally, all oil products plus natural gas are aggregated to avoid dealing with negative fuel consumption.

Summary: The following diagram summarizes the process.

Figure 3-51: Energy Balances process

3.9.3 Appendix C - Prices And Taxes Methodology

Energy prices and taxes are among the main inputs of the Mitigation module. They include information on (1) domestic energy prices by fuel and sector, (2) governmental price controls, (3) international energy prices and forecasts, and (4) existing carbon pricing mechanisms (carbon taxes and ETS). This document reflects the main principles and data sources used to

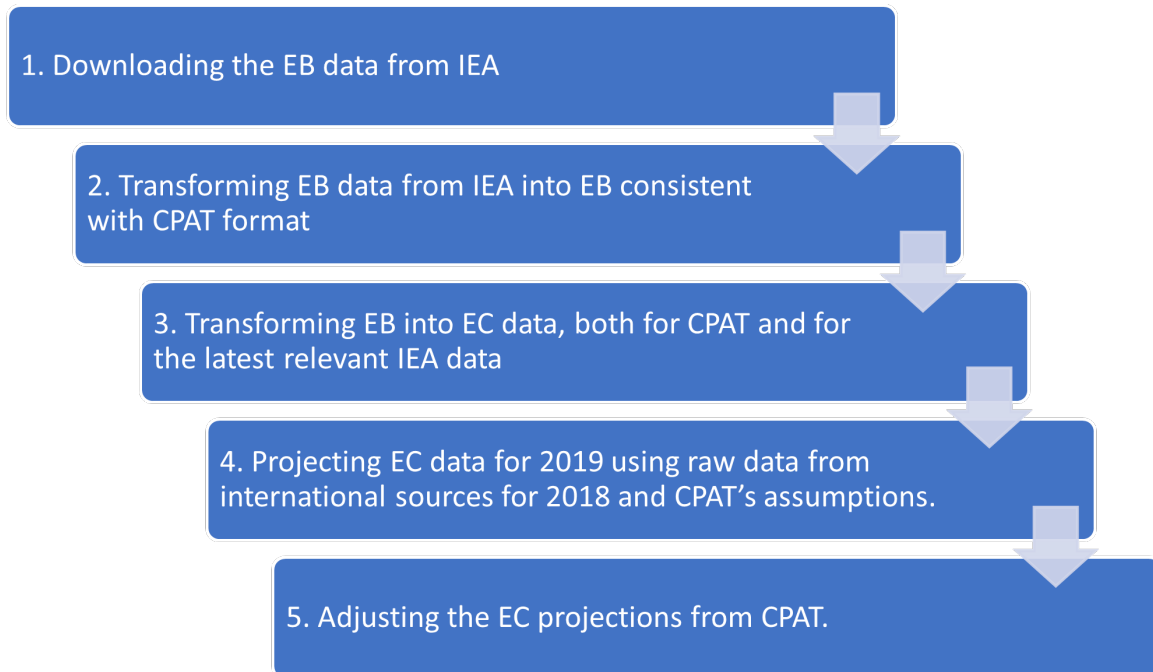


Figure 3.81: Figure 81: Energy Balances process

build the CPAT Prices and Taxes part of the Mitigation module, information on assumptions used in calculations, and the main outputs of the Mitigation module that directly depend on the prices and taxes data.

The main data sources for prices and taxes inputs include:

- For international energy price forecasts: energy price scenarios from the World Bank (Commodity Markets Outlook, “Pink Sheet” data), IMF (World Economy Outlook), IEA (World Energy Outlook), and EIA (International Energy Outlook);
- For domestic energy prices and forecasts: historical fuel- and sector-specific prices from Enerdata, IEA, IMF FAD, and other sources;
- For current carbon pricing mechanisms: historical and planned carbon taxation or ETS information, mainly based on the Carbon Pricing Dashboard;
- For subsidies: IMF Energy Subsidies Template, ODI, other data sources

Based on the historical data and policy specifications, including sub-sectoral exemptions, the Mitigation module calculates the changes in energy prices and their impact on energy consumption. These energy prices and their changes are used as inputs in the distributional and road transport modules.

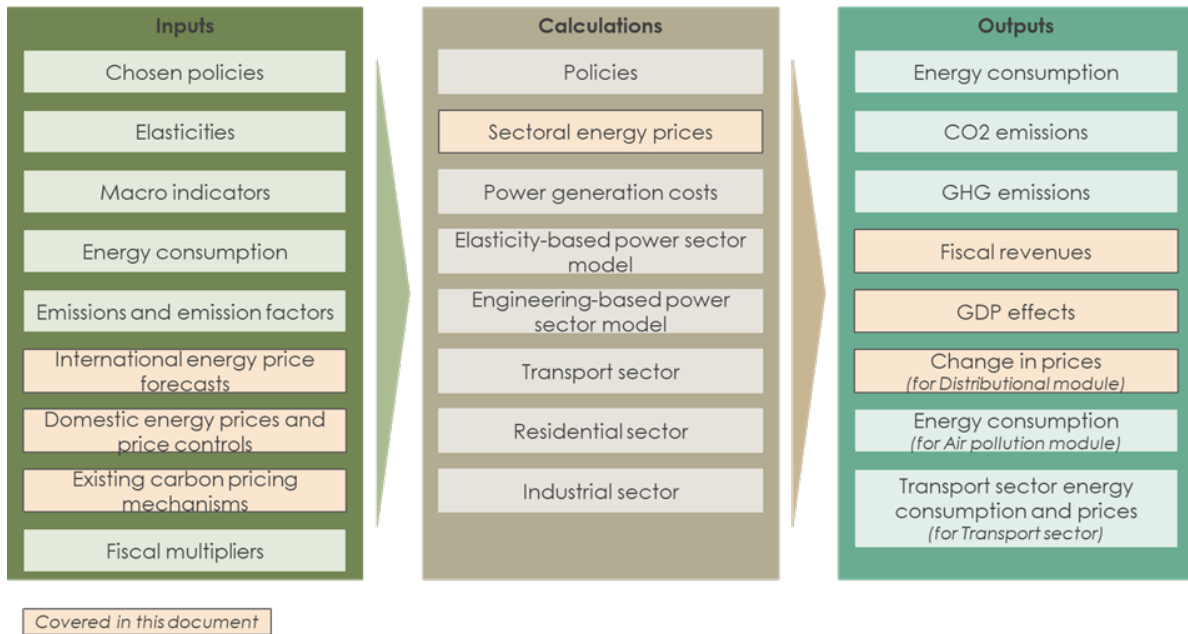


Figure 3.82: Mitigation module scheme: prices and taxes

3.9.3.1 User options affecting prices in CPAT

This section lists the user's choices and briefly explains how these choices will affect further calculations. For more details, please refer to specific parts of this document. See Figure 3.83 for a snapshot of the parameters affecting prices in CPAT.

3.9.3.1.1 Policy coverage and exemptions

The user can choose what fuels and sectors to tax on the Dashboard (see Figure 3.84). The fuels and sectors not selected would be exempted from the policy.

Additionally, the user decides whether to phase out exemptions or not and the period to phase out exemptions (see Figure 3.85).

Note: if the fuel is exempt and the phase-out is active, the carbon pricing policy (new carbon tax or ETS) will increase by $1/n$ every year starting from the year in which the policy would be introduced, where n is the number of years to phase out exemptions. The user can trace exemptions in the "New policy coverage: CO2 emissions covered" graph on the Dashboard.

3.9.3.1.2 Choices of the sources for key inputs

The user can choose the source for international and domestic energy prices:

1 Select country --> **Bulgaria**

2 Select policy --> **- Carbon tax**

3 Define policy --> Year to introduce new policy: **2022**
Starting carbon price (real USD per ton CO₂e): **0.0**
Target level of carbon price: **0.0**
Year to reach target level: **2030**

4 Select settings (defaults or manual) --> **Manual***

5 Policy coverage (for policies without pre-defined sectoral/fuel coverage)

Fuels: Coal Natural Gas Gasoline Diesel LPG Kerosene Other oil products

Sectors: Power Road Rail Domestic aviation Domestic shipping Residential Other energy use

Industries: Food & forestry Services (private & public) Mining & chemicals Iron & steel Other metals
 Machinery Cement Other manufacturing Construction Fuel transformation & transportation

6 Exemptions (fuels/sectors) --> Phaseout, starting in: **2022** **5** years to phase out (if applicable)

7 Fossil fuel subsidies (producer) --> Phaseout, starting in: **2022** **5**

8 Fossil fuel subsidies (consumer) --> Phaseout, starting in: **2022** **5**

9 Price controls (for fuels) --> Phaseout, starting in: **2022** **5**

10 Renewable subsidy --> €/kwh feed-in subsidy: **0.0** **10**

11 Revenue recycling --> 100% of revenues recycled

Labor tax reductions: **0** % revenues used to reduce labor taxes (SSC, PIT)

Corporate tax reductions: **0** % revenues used to reduce corporate income (CIT)

Public investment: **50** % on e.g. public transport, infrastructure

Current spending: **0** % on e.g. health, education, social security

Transfers: **50** % on transfer mechanisms (new lump-sum cash transfers)

of which: - targeted percentile: **40** % from bottom of income distribution targeted for transfers
- coverage rate: **100** % of targeted percentile that receive transfers
- leakage rate: **0** % of untargeted percentile that receive transfers

Key policy options: Sources for key inputs:

Additional mitigation effort in non-energy sector: **Yes*** International energy price forecasts: **AVG***

Price pathway continues to rise after target: **Linear*** GDP growth forecasts: **WEO***

Policy pathway is in nominal or real terms?: **Real*** Price elasticities of demand source: **Simple***

Power price: portion of cost change passed: **100%** Income elasticities of demand source: **Simple***

Power feebate: power revenues rebated: **No*** CO2 emissions factors: **IASA***

Phase out existing electricity taxes/subsidies: **No*** Fiscal multipliers: **Income-grp***

Harmonize VAT rates in residential and transport: **No*** Power sector model (elasticity or engineering?): **Average***

General assumptions

First year of model calculations? **2019**

Nominal results in real terms of which year? **2021**

Use energy balances or (CPAT) energy cost? **Balances**

Generate Matrix of Energy Consumption Profiles? **2019**

NDC submission: **Latest***

Use 'world' (USA) or country-specific discount rates? **World**

Sum all oil products in industrial transformation? **converted**

Adjust Annex I country energy-related CO2 emissions? **Yes***

Adjust non-Annex I country energy-related CO2 emissions? **Yes***

Info: adjustment to EFs: **0.99**

Industrial process emissions scale with industrial output? **Yes***

LULUCF emissions decline at % pa (in absolute terms)? **3%**

Global energy demand scenario: **Stated Policies***

Social cost of carbon (SCC) assumptions:

Target-consistent carbon price by 2030 (to 2022): **75**

NSCC discount rate (ρ): **2%**

NSCC elasticity of marginal utility (μ): **1.5%***

Global social cost of carbon (GSCC) source: **Target***

Manual - assumed starting in year 2021 (USD 2019): **50**

SCC (both NSCC and GSCC) - annual rise: **4%**

Additional policy-induced efficiency gains by sector:

Power: **0%**

Road vehicles: **0%**

Residential: **0%**

Industrial: **0%**

Feebates: **0%**

Other oil products: **0%**

LPG: **0%**

Energy efficiency regulations: **70%**

Vehicle fuel economy: **70%**

Residential efficiency regulations: **70%**

Industrial efficiency regulations: **70%**

Feebates: **100%**

Residential Substitution Implicit Efficiencies:

LPG: **56%**

Kerosene: **45%**

Biomass: **20%**

NatGas: **58%**

New ETS: **90%**

ETS behavioral responses and revenues adjustment: **50%**

Percent of industry that is covered by ETS: **50%**

Apply existing non-carbon taxes?

Coal: **Yes***

Natural gas: **Yes***

Gasoline: **Yes***

Diesel: **Yes***

Other oil products: **Yes***

LPG: **Yes***

Kerosene: **Yes***

Biomass: **Yes***

Electricity: **Yes***

Existing carbon tax

Apply existing carbon tax (if exists)? **Yes***

Assumed existing carbon tax growth per annum (in %): **0%**

Existing ETS

Apply existing ETS (if exists)? **Yes***

Existing ETS permit price growth per annum (real %): **0%**

New carbon tax complementary to existing ETS (if exists): **No***

Override base + 3 year with current/forecast: **No***

USD EU-ETS price in base + 3 year (projected two years before 2022): **0%**

Energy pricing assumptions

Use manual domestic energy prices? **No**

Use uniform global assumption for fuel prices (no externalities are part of VAT base for optimal tax)? **No**

Externalities are part of VAT base for optimal tax? **Yes***

Phase out Subsidies

Share of subsidies to phase-out in the policy scenario? **100%**

Apply phaseout in the baseline scenario? **No**

Period to reach full phaseout (baseline scenario): **5**

Share of subsidies to phase-out in the baseline scenario? **50%**

Consumer-side subsidy

Share of subsidies to phase-out: **100%**

Apply phaseout in the baseline scenario? **No**

Period to reach full phaseout (baseline scenario): **5**

Share of subsidies to phase-out in baseline: **50%**

Price liberalization

Government energy price controls: **None***

Phase-out price controls in the baseline? **No**

Figure 3.83: Dashboard parameters affecting prices

4 Carbon tax policy coverage (other policies have predefined coverage):

Fuels: Coal Natural Gas Gasoline Diesel LPG Kerosene Other oil products

Sectors: Power Road Rail Domestic aviation Domestic shipping Residential Other energy use

Industries: Food & forestry Services (private & public) Mining & chemicals Iron & steel Other metals
 Machinery Cement Other manufacturing Construction Fuel transformation & transportation

Figure 3.84: Dashboard: Policy coverage

6 Exemptions (fuels/sectors) --> Phaseout, starting in: **2022** **8**

7 Fossil fuel subsidies (producer) --> Phaseout, starting in: **2022** **5** years to phase out (if applicable)

8 Fossil fuel subsidies (consumer) --> Phaseout, starting in: **2022** **7**

9 Price controls (for fuels) --> Phaseout, starting in: **2022** **5**

10 Renewable subsidy --> €/kwh feed-in subsidy: **0.0** **10**

Figure 3.85: Dashboard: Exemptions

Sources for key inputs:	
International energy price forecasts	AVG*
GDP growth forecasts	WEO2020*
Primary source for price elasticities of demand	Simple*
Primary source for income elasticities of demand	Simple*
CO2 emissions factors	IIASA*

Figure 3.86: Dashboard: Sources for key inputs

The options for key inputs include “manual,” which the user can fill in a separate “Manual inputs” tab:

CPAT MANUAL INPUTS					Links → Dashboard				
Explanation: this table allows for more precise tweaking of inputs and assumptions where manual data is available									
NB: Please change only yellow cells. Make sure the units are correct.									
Domestic energy prices & taxes					Energy prices & taxes set to 'manual' (see Advanced options in Dashboard)				
Sector	Fuel	Variable	Units	Code	2017	2018	2019	2020	2021
Power sector	Coal	Supply costs	\$/GJ, current	mit.sp.coa.pow					
Power sector	Coal	Pre-tax subsidy	\$/GJ, current	mit.ps.coa.pow					
Power sector	Coal	VAT payment	\$/GJ, current	mit.vat.coa.pow					
Power sector	Coal	Excise and other taxes	\$/GJ, current	mit.bo.coa.pow					
Power sector	Coal	Retail price	\$/GJ, current	mit.rp.coa.pow					
Residential	Coal	Supply costs	\$/GJ, current	mit.sp.coa.res					
Residential	Coal	Pre-tax subsidy	\$/GJ, current	mit.ps.coa.res					
Residential	Coal	VAT payment	\$/GJ, current	mit.vat.coa.res					
Residential	Coal	Excise and other taxes	\$/GJ, current	mit.bo.coa.res					
Residential	Coal	Retail price	\$/GJ, current	mit.rp.coa.res					
Industry	Coal	Supply costs	\$/GJ, current	mit.sp.coa.ind					
Industry	Coal	Pre-tax subsidy	\$/GJ, current	mit.ps.coa.ind					
Industry	Coal	VAT payment	\$/GJ, current	mit.vat.coa.ind					
Industry	Coal	Excise and other taxes	\$/GJ, current	mit.bo.coa.ind					
Industry	Coal	Retail price	\$/GJ, current	mit.rp.coa.ind					

Figure 3.87: Manual inputs

3.9.3.1.3 Policy options: Existing carbon pricing policies

The user can choose to apply existing carbon tax or ETS (if they exist) on the Dashboard:

When there is a previous carbon tax or ETS in place, the user also has an option to specify the price growth for future years in the “Advanced options” of the Dashboard:

Please note the following:

- Even if the user decides not to apply existing carbon pricing mechanisms, it will not affect historical prices, only forecasted.
- Existing policy coverage for carbon tax and ETS permit prices are fractional. When considering sector and fuel coverage, for existing policies, CPAT accounts for the fraction of the consumption that is affected by the policy. This differs from the treatment of coverage under the new, user-defined, policies. There, the option to include or not a sector or fuel is binary. For new policies, a fractional coverage only occurs when the user selects to exempt a sector or fuel, and to phase out that exemption in time.

Existing carbon tax	
Apply existing carbon tax (if exists)?	Yes*
Assumed existing carbon tax growth per annum (real term)	0%
Existing ETS	
Apply existing ETS (if exists)?	Yes*
Existing ETS permit price growth per annum (real term)	0%
New carbon tax complementary to existing ETS coverage	No*

Figure 3.88: Dashboard: Policy Options

Existing carbon tax	
Apply existing carbon tax (if exists)?	Yes*
Assumed existing carbon tax growth per annum (real term)	0%
Existing ETS	
Apply existing ETS (if exists)?	Yes*
Existing ETS permit price growth per annum (real term)	0%

Figure 3.89: Dashboard: Advanced Policy Options

3.9.3.1.4 Policy options: New excise / existing excise exemptions

The user can add a manual per-unit of energy excise, by choosing the “Add additional excise” option on the Dashboard and filling a relevant part of the “Manual inputs” tab.

Policy options:	
Additional mitigation policies in non-energy sector?	Yes*
Apply existing ETS (if exists)?	Yes*
Apply existing carbon tax (if exists)?	Yes*
Add additional excise tax (see 'Manual inputs' tab)	No*
Phase out existing electricity taxes/subsidies?	No*

Figure 3.90: Manual inputs: Manual Policy Options

The user also has an option not to apply existing excise taxes starting from the policy year (existing excises are applied by default):

Apply existing non-carbon taxes?			
Coal		coa	Yes*
Natural gas		nga	Yes*
Gasoline		gso	Yes*
Diesel		die	Yes*
Other oil products		oop	Yes*
LPG		lpg	Yes*
Kerosene		ker	Yes*
Biomass		bio	Yes*
Electricity		ele	Yes*

Figure 3.91: Dashboard: Existing tax removal

Please note:

- If the user decides not to apply existing non-carbon taxes, this decision will affect only policy forecast, not baseline and historical data. Moreover, if the user decides to keep existing policies in place, by default those will be projected with the existing sector and fuel coverage and not with the one the user may use for newly-introduced policies.
- As discussed before, existing policy coverage for carbon tax and ETS permit prices are fractional, while the coverage for new policies is binary. Indeed, when considering sector and fuel coverage, for existing policies, CPAT accounts for the fraction of the consumption that is affected by the policy. This differs from the treatment of coverage under the new, user-defined, policies. There, the option to include or not a sector or fuel is binary. For new policies, a fractional coverage only occurs when the user selects to exempt a sector or fuel, and to phase out that exemption in time.

3.9.3.1.5 Policy options: VAT reforms

The user can include externalities to be part of the VAT base for optimal taxation (included by default):

Energy pricing assumptions	
Use manual domestic energy prices?	No
Use uniform global assumption for fuel prices (norm	No
Externalities are part of VAT base for optimal taxes?	Yes*

Figure 3.92: Dashboard: VAT Reform

Also, the user can choose to apply the same VAT tax rate in the residential and transport sectors if it is different from the general VAT in the economy (“advanced options” in the Dashboard):

Key policy options:	
Additional mitigation effort in non-energy sectors?	Yes*
Price pathway continues to rise after target year?	Linear*
Policy pathway is in nominal or real terms?	Real*
Power price: portion of cost change passed-on:	100%
Power feebate: power revenues rebated per kwh	No*
Phase out existing electricity taxes/subsidies?	No*
Harmonize VAT rates in residential and transport?	No*

--> more advanced policy options

Figure 3.93: Dashboard: Adjusting VAT per sector

3.9.3.1.6 Fossil fuel subsidies reform

The user can choose to phase out fossil fuel subsidies (producer- and/or consumer-side) over a specified period (n years). The fossil fuel subsidy will decrease linearly by $1/n$ every year starting from the year the user chose to start the phase-out until they reach zero or a specified limit.

Additionally, the user can choose to phase out only a part of the fossil fuel subsidies in the “advanced options” of the Mitigation module.

6 Exemptions (fuels/sectors) -->	<input type="checkbox"/> Phaseout, starting in:	2022	8	years to phase out (if applicable)
7 Fossil fuel subsidies (producer) -->	<input checked="" type="checkbox"/> Phaseout, starting in:	2022	5	
8 Fossil fuel subsidies (consumer) -->	<input checked="" type="checkbox"/> Phaseout, starting in:	2022	7	
9 Price controls (for fuels) -->	<input type="checkbox"/> Phaseout, starting in:	2022	5	

Figure 3.94: Dashboard: Fossil Fuel Subsidies Reform

Producer-side subsidy	
Share of subsidies to phase-out in the policy scenario	100%
Apply phaseout in the baseline scenario?	No
Period to reach full phaseout (baseline scenario)	5
Share of subsidies to phase-out in the baseline scenario	100%
Consumer-side subsidy	
Share of subsidies to phase-out in the policy scenario	100%
Apply phaseout in the baseline scenario?	No
Period to reach full phaseout (baseline scenario)	5
Share of subsidies to phase-out in baseline	100%

Figure 3.95: Dashboard: Fossil Fuel Subsidies Reform (Advanced Mitigation Options)

3.9.3.1.7 Price liberalization

The user can choose to calculate the impact of the government energy price control in the “advanced options” of the Dashboard and the source for price control coefficients (manual or regional). The choice will not affect historical price components but will affect calculations of fiscal revenues or losses.

Price liberalization	
Government energy price controls	None*
Phase-out price controls in the baseline?	No

Figure 3.96: Dashboard: Price liberalization (Advanced Mitigation Options)

Note. Do not use price liberalization and fossil fuels subsidies phase out simultaneously to avoid double-counting.

3.9.3.2 Price components

3.9.3.2.1 Assumed pricing mechanism

Figure 3.97 below presents the main components of fuel prices in CPAT.

Supply price is an average price that includes all price components like production and transformation costs, transportation and distribution costs, profits, and others, except taxes.

Retail price is an average end-user price paid by the final user in the corresponding sector (power generation, industry, transport, residential) per unit of energy, including all applicable taxes and subsidies. According to IEA, the historical retail prices are calculated as a ratio of total sales of energy to the sold volume. The retail price should equal the supply price plus all relevant taxes:

$$p_{cgf,t} = sp_{cgf,t} + ttx_{cgf,t}$$

where p is the average retail price, sp is the price before net taxes and ttx are the total net taxes for country c , fuel f in sector group g and year t . This holds for both the baseline and the policy scenarios.

Note: In general, carbon pricing policies and the phasing out of consumer-side subsidies will affect the ttx component, while the phasing out of existing producer-side subsidies will instead affect the supply price sp .

Price gap/total taxes/subsidy: the gap between the supply cost and retail price. This is a function of any type of taxation and/or subsidization that causes the supply cost to

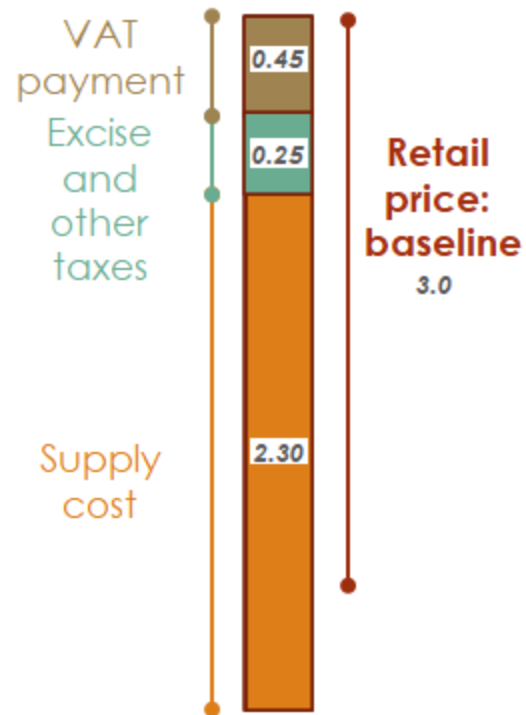


Figure 3.97: Main components of baseline prices

deviate from the import/export parity price plus mark-ups and the any taxes applied to the price before tax, such as VAT, excise taxes, and other taxes (environmental, renewable support taxes, energy security taxes, social taxes, and others). The historical values of ttx are calculated in the dataset as a difference between average retail price and price before taxes and, thus, are negative in the case of a net subsidy. For forecasted years, the value of ttx will instead be computed as the sum of the forecasted subcomponents (different types of taxes and consumer-side subsidies).

$$ttx_{cgf,t} = p_{cgf,t} - sp_{cgf,t}$$

where ttx stands for the total net taxes (or net subsidy if negative), p is the average retail price and sp is the supply price (i.e. the price before tax). By construction, this relationship holds for all scenarios. Moreover, the total net taxes are further decomposed into VAT payment, and excise and other taxes.

VAT payment: it is computed by obtaining the portion of the retail price that corresponds to VAT payment given a known country-or-sector-specific VAT rate. For the forecasting period, the VAT payment is calculated as VAT base (price before tax plus all other taxes except VAT) multiplied by the VAT rate.

$$vat_{c,f,g,t} = (sp_{c,f,g,t} + txo_{c,f,g,t}) * vatraterate_{c,f,g,t}$$

where VAT is the VAT payment per energy unit, txo represents the excise and other taxes/subsidies and $VATrate$ is the VAT rate.

The VAT rate is assumed to be 0 for industrial and power generation users since these users receive a credit on their input VAT. Similarly, for fuels for which a unique price is reported for all sectors, the VAT payment obtained above is adjusted by the share of residential over total consumption to ensure only final purchases are charged.

Excise and other taxes: calculated in the historical dataset as a the portion of retail price not explained by supply cost or VAT payment.

$$txo_{cgf,t} = p_{cgf,t} - sp_{cgf,t} - vat_{cgf,t}$$

For the forecasted years, instead, it is computed as the sum of its projected components. This, as in the scenarios we decompose the Excise and other taxes category into several additional price components, such as *current carbon tax*, *current ETS permit price*, *new policy*, *new excise tax (if applicable)*, as well as the floating or fixed portions of both subsidies and taxes.

- Existent carbon tax/ETS permit price: ‘effective’ carbon tax/ETS permit price as a component of total taxes is calculated separately in CPAT based on existing carbon pricing mechanisms and emission factors. Details are provided below.

- New policy/new excise tax: the main driver of the change in retail prices. They are calculated as components of the excise and other categories, depending on the chosen policy (new carbon tax, ETS, road fuel tax, others), the policy coverage, and emission factors. By default, in the baseline scenario, new policy/new excise taxes are equal to zero.
- Floating and fixed proportions of subsidies and taxes: computed depending on historical data and on the (phasing-out of) existing price controls or subsidies.

3.9.3.2.2 Assumptions used for price reconstruction and projections

Retail prices:

- Takes user-provided data if there is any in the ‘manual inputs’ tab
- Uses CPAT generated prices if the data exist
- Otherwise, calculated as a sum of the supply cost, VAT and other (excise + environmental) taxes

Supply price:

- Takes user-provided data if there is any in the ‘manual inputs’ tab
- Uses CPAT generated prices if the data exist
- Otherwise:
 - For the first year: if no data whatsoever, uses the global (regional if possible) price.
 - For the second year and after, calculated as a sum of its components: *Fixed and Floating portions of the supply price, as well as any existing producer-side subsidies.*

VAT payments:

- Takes user-provided data if there is any in the ‘manual inputs’ tab.
- Uses CPAT generated prices if the data exist.
- Otherwise:
 - For the power and industry sectors, assumes 0
 - for the residential and “all” sectors, computed as the fraction of the retail price consistent with the known VAT rate for that country and fuel.

Excise and other taxes:

- Takes user-provided data if there is any in the ‘manual inputs’ tab.
- Uses CPAT generated prices if the data exist.

Current carbon tax and ETS permit price: Uses CPAT generated prices if the data exist.

3.9.3.3 Forecasted prices (after 2021)

3.9.3.3.1 Calculations: Modeling assumptions

For years starting from 2023, the price components are modeled by following rules.

Retail price for fuel f in sector grouping g in year t is a sum of the supply price (sp) and all applicable taxes: VAT payments (vat), and excise and other taxes (txo):

$$p_{cgf,t} = sp_{cgf,t} + vat_{cgf,t} + txo_{cgf,t}$$

Supply price for fuel f in sector grouping g in year t is calculated as a sum of its components:

$$sp_{cgf,t} = fixsp_{cgf} + fltsp_{cgf,t} + ps_{cgf,t}$$

where $fixsp$ and $fltsp$ stand for the fixed and floating portions of the supply price, respectively, and ps represents the outstanding producer-side subsidy

Fixed portion of supply price represents the margins charged on top of international prices or production costs. They are set to remain at the average value observed during the historical years t_0 (2018-2022):

$$fixsp_{cgf} = \frac{1}{n_{t_0}} \sum_{t_0=2018}^{2022} fixsp_{cgf,t_0}$$

Floating portion of supply price represents all fluctuations of the supply price during the historical years (2018-2022) that are not explained by the fixed portion nor by the producer-side subsidy. For the forecasted period, they are assumed to be evolve at the same pace as the international prices (gp):

$$fltsp_{cgf,t} = fltsp_{cgf,t-1} \times \frac{gp_{cgf,t}}{gp_{cgf,t-1}}$$

Producer-side subsidies, if exist, can be phase-out by the user as part of the policy design so that:

$$ps_{cgf,t} = ps_{cgf,t-1} \times \phi_{PS,t}$$

where $\phi_{PS,t}$ is the phase-out factor for period t , corresponding to the user-defined trajectory.

VAT payment, as for the historical years, is obtained by the product of the VAT base (supply cost plus excise and other taxes), and the VAT rate

$$vat_{c_{fg},t} = (sp_{c_{fg},t} + txo_{c_{fg},t}) * vatrater_{c_{fg},t}$$

where VAT is the VAT payment per energy unit, txo represents the excise and other taxes/subsidies and $VATrate$ is the VAT rate.

The VAT rate is assumed to be 0 for industrial and power generation users since these users receive a credit on their input VAT. Similarly, for fuels for which a unique price is reported for all sectors, the VAT payment obtained above is adjusted by the share of residential over total consumption to ensure only final purchases are charged.

Excise and other taxes are computed as the sum of multiple components for each country c , sector group g , fuel f and period t :

$$txo_{c_{fg},t} = fixtax_{c_{fg},t} + fixsub_{c_{fg},t} + flts_{c_{fg},t} + xct_{c_{fg},t} + xetsp_{c_{fg},t} + nct_{c_{fg},t} + netsp_{c_{fg},t} + nexc_{c_{fg},t}$$

where $fixtax$ and $fixsub$ correspond to the fixed portions of taxes and subsidies, respectively, and $flts$ stands for the net floating portion of tax or subsidies. The remaining components stand for the existing (xct and $xetsp$) and new (nct and $netsp$) carbon taxes and ETS permit prices respectively, as well as any new excise taxes introduced as part of the policy, $nexc$.

Fixed portion of taxes are assumed to remain constant. For any period, their value corresponds to the average value observed during the historical years:

$$fixtax_{c_{fg},t} = fixtax_{c_{fg},t_0}$$

Fixed portion of subsidies correspond to the outstanding fixed portion of subsidies (average of historical years) after the phasing out of subsidies has been considered.

$$fixsub_{c_{fg},t} = fixsub_{c_{fg},t_0} \times \phi_{CS,t}$$

where $\phi_{CS,t}$ stands for the phase-out factor for consumer-side subsidies for year t corresponding to the user-defined trajectory.

Floating portion of subsidy/tax is forecasted based on the observed average for the historical years, adjusted by the gap between the current supply price and its own average during historical years. This is then adjusted by the phase-out factor for price controls:

$$flts_{c_{fg},t} = \left(\frac{\sum_{t_0=2018}^{2022} flts_{c_{fg},t_0}}{n_{t_0}} + \frac{\sum_{t_0=2018}^{2022} sp_{c_{fg},t_0}}{n_{t_0}} - sp_{c_{fg},t} \right) \times (1 - pcc) \times \phi_{PC,t}$$

where pcc represents the price control coefficient, and ϕ_{PC_t} stands for the phase out factor for existing price controls.

Current carbon tax and ETS permit price are read from the historical dataset and adjusted based on user-defined options. If the user decides to apply existing carbon pricing mechanisms, the values will be calculated based on historical values and planned policies. If a country's carbon pricing policy is not specified for years after 2020, the current carbon tax / ETS permit price per energy unit, xcp , is calculated as:

$$\begin{aligned} xcp_{cgf,t} &= xct_{cgf,t} + xetsp_{cgf,t} \\ &= xct_{cgf,t_0} * (1 + \delta_{CT})^{t-t_0} + xetsp_{cgf,t_0} * (1 + \delta_{ETS})^{t-t_0} \\ &= XCT_{c,t_0} * ef_{cgf} * \varphi_{XCT,cgf,t_0} * (1 + \delta_{CT})^{t-t_0} + \\ &\quad XETSP_{c,t_0} * ef_{cgf} * \varphi_{XETSP,cgf,t_0} * (1 + \delta_{ETS})^{t-t_0} \end{aligned}$$

As show above, the existing carbon price per energy unit results from scaling the existing carbon taxes and ETS permit prices from the base year, XCT and $XETSP$ respectively, by their specific coverage φ , the fuel-sector-specific emissions factor ef , and the user-defined growth rate of the nation-wide price for the forecasted years δ .

New carbon prices result from simulated policies. At the current stage, these are represented by the application of either carbon taxes or ETS permit prices. As such, they rely on the level of the carbon price set per ton of CO₂ equivalent emissions, scaled by the relevant emission factors, and adjusted by the defined coverage by fuel and sector.

$$\begin{aligned} ncp_{cgf,t} &= nct_{cgf,t} + netsp_{cgf,t} \\ &= NCT_{c,t} * ef_{cgf} * \varphi_{NCT,cgf,t} + \\ &\quad NETSP_{c,t} * ef_{cgf} * \varphi_{NETSP,cgf,t} \end{aligned}$$

where $nct_{cgf,t}$ and $netsp_{cgf,t}$ stand for the new carbon tax per energy unit and the new ETS price per energy unit, respectively. In both cases, the value per energy unit is obtained based on the national price per ton of CO₂ ($NCT_{c,t}$ or $NETSP_{c,t}$), and scaling it by the country-sector-fuel specific emission factors, $ef_{cgf,t}$, and the sector-fuel coverage for the new policies within the country in question ($\varphi_{NCT,cgf,t}$ and $\varphi_{NETSP,cgf,t}$).

Among the options available, the user can select the sectors or fuel that will be exempt of the policy implemented, as well as the linear phase out of those exemptions, if selected by the user. This is already considered in the sector-fuel coverage φ .

New excise tax ($nexc_{cgf,t}$) can be defined by the user, who is able to specify additional per energy unit excise tax in the "Manual inputs" tab.

3.9.3.4 Power generation costs

Please note that the ‘old’ cost model from IMF paper is used only in the elasticity-based power model, and only if ‘Old’ costs are selected (See Figure 3.98).

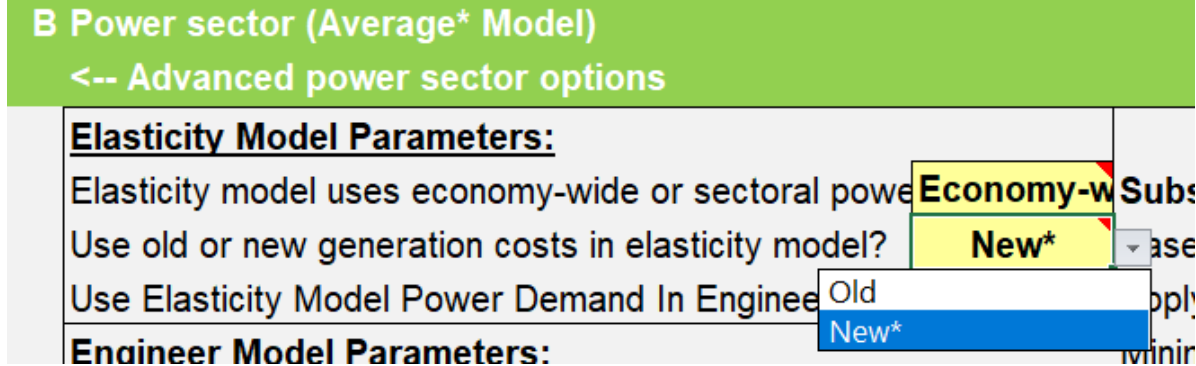


Figure 3.98: Generation costs in the elasticity model

Elasticity-based generation costs are defined as follows. The total unit costs of generation (i.e. for each fuel type considered), gnc_{ocft} , is estimated as:

$$gnc_{ocft} = efc_{ocft} + nfc_{ocft} + rps_{o,cgft} + nct_{P,cgft} * (1 - tex_{P,tcft})$$

where:

- efc_{ocft} denotes the effective fuel unit costs (i.e. after autonomous efficiency gains), which is defined as the retail price before any new policies adjusted from the autonomous efficiency improvement in generation.
- nfc_{ocft} is the effective non-fuel unit costs (i.e. after autonomous efficiency gains). For the base year, non-fuel unit cost is assumed as a fixed proportion through the period of costs that are non-fuel, γ :

$$nfc_{ocf,t_0} = \frac{efc_{ocf,t_0}}{(1 - \gamma)} * \gamma$$

For the following years, effective non-fuel unit costs are equal to effective non-fuel costs from the previous year, adjusted from the autonomous efficiency improvement.

- $rps_{o,cgft}$ denotes the renewable producer subsidies, which only apply to wind, solar, hydro and other renewables.

3.9.3.5 New price target: Goal seek

When simulating the introduction of a new ETS permit, CPAT allows the user to define, among others, the year of implementation, the initial price/tax to be considered, and the level at which it should reach in a ‘target’ year. While still on a development phase, CPAT incorporates a ‘goal seek’ feature to help the user determine the new policy’s target price based on an goal on the emissions level.

ETS Goal Seek					
Target Carbon Price (Linked to cell I6)				\$	50.0
Sectoral Inclusion:					
Power sector				Yes	
Transport				Yes	
Buildings				Yes	
Industry				Yes	
Other				No	
If yes, proportion of Industry Sector				1	
Percentage or Absolute Target?				AbsTarget	
Percentage change (usually -ve)				-0.25	
Absolute target				295	
Goal Seek	Included	Baseline	Policy Scen.	Proportion In Policy Actual	Diff Squared
Power sector	Yes	0.0	0.0	1	
Transport	Yes	8.9	8.1	1	
Residential	Yes	0.3	0.3	1	
Industry	Yes	0.2	0.2	1	
Other	No	0.0	0.0	0	
Total		9.5	8.6		295 82044.47404

Figure 3.99: ETS target price - Goal Seek

Located to the right of the Advanced Options in the dashboard, the goal seek allows the user to input:

- The sectoral inclusion
- The proportion of the industrial sector to be covered (if Industry is included)
- The emissions target (in absolute terms, or the reduction percentage)

The lower part of the goal seek shows the emissions, by sector, for the baseline and the policy scenarios. The ‘Total’ row shows, first, the aggregated emissions (considering only the sectors

included by the user), second, the emissions goal, and third, the squared difference of emissions between the baseline and the policy scenario.

While the user can apply the goal seek functionality in Excel, the algorithm is not particularly useful in this case, and it is more convenient to test the different target prices manually, step-by-step.

In brief, once the inputs of the Goal Seek feature are provided, the user should check different alternatives of a target price and evaluate how emissions perform under each one. This simplified tool aims at giving a broad approximation of the price level required to achieve the emissions goal for the target year.

3.9.4 Appendix D - Examples of NDCs calculations

3.9.4.1 Example 1: Paraguay (BaU NDC)

NDC overview:

- Unconditional target: 10% reduction relative to baseline emissions by 2030
- Conditional target: 20% reduction relative to baseline emissions by 2030
- GHG covered: CO₂, CH₄, N₂O
- LULUCF emissions: included

Calculations in CPAT:

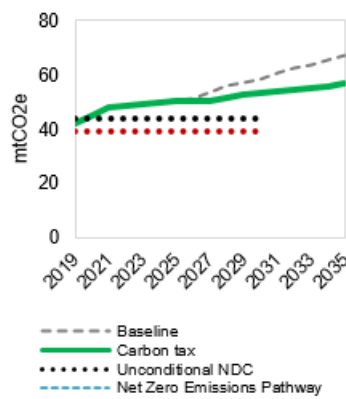
- Baseline GHGs, excl. LULUCF in 2030: 48.8 MtCO₂e
- Baseline GHGs, incl. LULUCF in 2030: 94.9 MtCO₂e

Based on NDC targets:

- Unconditional NDC target: 10% reduction relative to baseline emissions by 2030 * GHG excluding LULUCF: $48.8 * (1 - 10\%) = 43.9$ MtCO₂e
 - GHG including LULUCF: $94.9 * (1 - 10\%) = 85.4$ MtCO₂e
- Conditional NDC target: 20% reduction relative to baseline emissions by 2030
 - GHG excluding LULUCF: $48.8 * (1 - 20\%) = 39.0$ MtCO₂e
 - GHG including LULUCF: $94.9 * (1 - 20\%) = 75.9$ MtCO₂e

Figure 3-69: Rebound effect from exogenous efficiency improvements (% of emissions reduction reduced)

**GHG emissions vs. Paris pledge
(‘NDC’; mtCO₂e exc LULUCF),
Paraguay**



Latest NDC for Paraguay is a limit of 92.287 mt CO₂e by 2030 including LULUCF. Policy achieves 9.4% vs. BAU in 2030, which is 29.8% of the emissions reductions vs. BAU for NDC. Assumes non-LULUCF emissions fall at same rate as LULUCF emissions.

Figure 3.100: Figure 99: Rebound effect from exogenous efficiency improvements (% of emissions reduction reduced)

3.9.4.2 Example 2: Colombia (fixed NDC)

NDC overview:

- Unconditional target: 169.44 MtCO₂e in 2030
- Conditional target: N/A
- GHG covered: CO₂, CH₄, N₂O, HFCs, PFCs, SF₆ and black carbon
- LULUCF emissions: included

Calculations in CPAT:

- Baseline GHGs, excl. LULUCF in 2030: 218.8 MtCO₂e
- Baseline GHGs, incl. LULUCF in 2030: 302.6 MtCO₂e

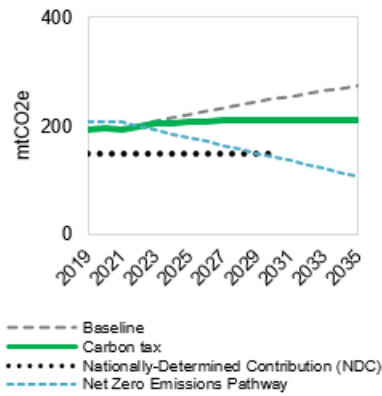
Based on NDC targets:

- Unconditional NDC target: 169.44 MtCO₂e (including LULUCF) in 2030
 - GHG excluding LULUCF: $169.4 - (302.6 - 218.8) = 85.6$ MtCO₂e
 - GHG including LULUCF: 169.4 MtCO₂e
- Reformatting to baseline reductions in 2030:
 - GHG excluding LULUCF reduction: $1 - \frac{(85.6)}{218.8} = 60.9$
 - GHG including LULUCF reduction: $1 - \frac{(169.4)}{302.6} = 44.0$
- Since NDC included LULUCF, we use 44% reduction as a target:
 - GHG excluding LULUCF target level: $218.8 * (1 - 44\%) = 122.5$ MtCO₂e

Figure 3-70: Rebound effect from exogenous efficiency improvements (% of emissions reduction reduced)

NB: CPAT models the impact of carbon pricing on energy-related emissions. Colombia's LULUCF emissions are 83.8 MtCO₂e, about a half of GHG emissions target in 2030. The harmonized calculations would imply a high burden on energy sector to achieve NDC goals. However, the user should also consider measures that the country would take in other sectors (agriculture, forestry, land use, sectoral policies) to achieve NDC goals.

**GHG emissions vs. Paris pledge
(‘NDC’; mtCO₂e exc LULUCF),
Colombia**



Latest NDC for Colombia is a limit of 169.44 mt CO₂e by 2030 including LULUCF. Policy achieves 15.4% vs. BAU in 2030, which is 32.5% of the emissions reductions vs. BAU for NDC. Net zero target for 2050 is declaration / pledge (illustrative linear pathway shown). Assumes non-LULUCF emissions fall at same rate as LULUCF emissions.

Figure 3.101: Figure 100: Rebound effect from exogenous efficiency improvements (% of emissions reduction reduced)

3.9.4.3 Example 3: Australia (historical NDC)

NDC overview:

- Unconditional target: 26-28% reduction relative to 2005 emissions levels
- Conditional target: N/A
- GHG covered: CO₂, CH₄, N₂O, HFCs, PFCs, SF₆ and NF₃
- LULUCF emissions: included

Calculations in CPAT: * 2005 GHGs, excl. LULUCF: 526.2 MtCO₂e * 2005 GHGs, incl. LULUCF: 617.2 MtCO₂e * Baseline GHGs, excl. LULUCF: 568.5 MtCO₂e * Baseline GHGs, incl. LULUCF: 546.0 MtCO₂e

Based on NDC targets:

- Unconditional NDC target: 28% reduction relative to 2005 levels:
- GHG excluding LULUCF: $526.2 * (1 - 28\%) = 378.8$ MtCO₂e
- GHG including LULUCF: $617.2 * (1 - 28\%) = 444.4$ MtCO₂e
- Reformatting to baseline reductions in 2030: * GHG excluding LULUCF reduction: $1 - \frac{378.8}{568.5} = 33.4\%$ * GHG including LULUCF reduction: $1 - \frac{444.4}{546.0} = 18.6\%$
- Since NDC included LULUCF, we use 18.6% reduction as a target:

$$- \text{GHG excluding LULUCF target level: } 568.5 * (1 - 18.6\%) = 462.7 \text{ MtCO}_2\text{e}$$

Figure 3-71: Rebound effect from exogenous efficiency improvements (% of emissions reduction reduced)

3.9.4.4 Example 4: Uruguay (intensity NDC)

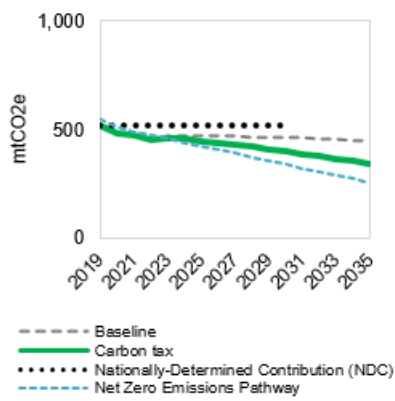
NDC overview:

- Unconditional target: 24% reduction in emissions intensity relative to 1990
- Conditional target: 29% reduction in emissions intensity relative to 1990
- GHG covered: CO₂
- LULUCF emissions: excluded

Calculations in CPAT: * 1990 CO₂ emissions intensity: 4.62 (tCO₂e/LCU) * 2030 baseline CO₂ emissions intensity: 3.593 (tCO₂e/LCU) * 2030 baseline GHG emissions, excl. LULUCF: 37.4 MtCO₂e

Based on NDC targets: * Unconditional NDC target: 24% reduction in emissions intensity relative to 1990 levels: * CO₂ intensity: $4.62 * (1 - 24\%) = 3.51$ MtCO₂e * Conditional NDC target: 29% reduction in emissions intensity relative to 1990 levels: * CO₂ intensity: $4.62 * (1 - 29\%) = 3.29$ MtCO₂e

**GHG emissions vs. Paris pledge
(‘NDC’; mtCO₂e exc LULUCF),
Australia**

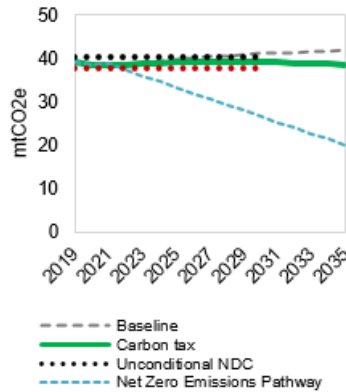


Latest NDC target for Australia is a 27% reduction in absolute emissions by 2030 vs. 2005. Target is achieved in the baseline. Net-zero target for 2050 is in policy document (illustrative linear pathway shown). Assumes non-LULUCF emissions fall at same rate as LULUCF emissions.

Figure 3.102: Figure 101: Rebound effect from exogenous efficiency improvements (% of emissions reduction reduced)

$(1 - 29\%) = 3.28 \text{ MtCO}_2\text{e}$ * Reformatting to baseline reductions in 2030: * Unconditional CO2 intensity reduction: $1 - \frac{3.509}{3.593} = 2.4\%$ * Conditional CO2 intensity reduction: $1 - \frac{3.28}{3.593} = 8.8\%$ * Converting to GHG emissions reduction goal: * Unconditional GHG excluding LULUCF target level: $37.4 * (1 - 2.4\%) = 36.5 \text{ MtCO}_2\text{e}$ * Conditional GHG excluding LULUCF target level: $37.4 * (1 - 8.8\%) = 34.1 \text{ MtCO}_2\text{e}$

GHG emissions vs. Paris pledge ('NDC'; mtCO₂e exc LULUCF), Uruguay



First NDC target for Uruguay is a 24% reduction and a 29% conditional reduction in emissions intensity of GDP (ceiling) by 2025. Conditional NDC is conditional on climate finance. Policy achieves 1.7% vs. BAU in 2030, which is 76.7% of the emissions reductions vs. BAU for NDC. Net-zero target for 2050 is in policy document (illustrative linear pathway shown).

Figure 3.103: Figure 102: Rebound effect from exogenous efficiency improvements (% of emissions reduction reduced)

Figure 3-72: Rebound effect from exogenous efficiency improvements (% of emissions reduction reduced)

3.9.5 Appendix E – Defaults and parameter options in the mitigation module

These tables show the different parameter options related to the mitigation module in the dashboard of CPAT.

This tables presents the **general settings**.

← More detailed options		Sources for key inputs:			Links to charts →		Mitigation	Distribution	Air pollution	Transport
16	Key policy options:									
17	Additional mitigation effort in non-energy sectors?	Yes*	International energy price forecasts	IMF-WB*	International energy prices adjustment	Base*	Include endogenous GDP effects?			Yes*
18	Price pathway continues to rise after target year?	Linear*	GDP growth forecasts	WEO*	GDP growth adjustment	Base*	Residential LPG/kerosene always exempted			No*
19	Policy pathway is in nominal or real terms?	Real*	Price elasticities of demand source	Simple*	Price elasticities adjustment	Base*	National social cost of carbon (SCC) source			Target*
20	Power price: portion of cost change passed-on:	100%	Income elasticities of demand source	Simple*	Income elasticities adjustment	Base*	Congestion & road damage attributable to fuels			1%
21	Power feebate: power revenues rebated per kWh	Yes	CO2 emissions factors	IASA*	Adjust income elasticities for GDP levels?	Yes*	Add non-climate Pigouvian tax on top?			No*
22	Harmonize VAT rates in residential and transport?	No*	Fiscal multipliers	Income-grp*	Fiscal multipliers adjustment	Base*	Years to phase-in non-climate Pigouvian tax?			5
23	Exempt/include Power from subsidy phase out	Include*	Power sector model (elasticity or engineer)?	Engineer	Max RE scaleup rate	CityDefault*	Add additional excise tax (see 'Manual inputs' tab)?			No*
24										
25										

Figure 3.104: Dashboard: General settings

Settings	Defaults (*) and ad- di- tional op- tions	Description
Key pol- icy op- tion		
Additional mit- i- ga- tion ef- fort in non- energy sec- tors?	Yes*/No/Manual	Whether complementary policies are implemented alongside the main policy to target GHGs in non-energy sectors (industrial processes, agriculture, LULUCF, waste, and fugitive emissions). No macro/welfare effects are estimated.

Settings	Defaults (* and ad- di- tional op- tions	Description
Price pathway continues to rise after target year?	Linear*/No/Percentage	No = policy remains flat after target year Linear = price continues to rise in a linear manner after target year Percentage = price continues to rise at the same % growth rate in the target year of the linear pathway
Policy pathway is in nominal or real terms?	Real*/Nominal	If nominal, tax rate reduces with inflation.

Settings	Defaults (* and ad- di- tional op- tions	Description
Power price: portion of cost change passed-on:	1*/0.75/0.5/0.25/0	The portion of the increase in generation costs from the policy that are passed on in consumer prices. <1.0 for e.g. countries with state-owned utilities where the utility is not allowed to pass-on input cost increases to retail electricity prices.
Power fee-bate: power revenues re-bated per kwh	No*/Yes	If selected, this means revenues raised from additional taxes/ETSs in power sector are kept within the sector through an output-based rebate to generators.
Phase out existing electricity taxes/subsidies?	No*/Yes	If there are existing electricity taxes or subsidies, phases them out over the same time period as fossil fuel subsidies (defined above). For mitigation purposes it is preferable to tax the fuels going into electricity generation rather than the electricity itself, which could be sourced from renewables as well as fossil fuels.

Settings	Defaults (* and ad- di- tional op- tions	Description
Harmonize VAT rates in residential and transport?	No*/Yes	Applies general economy's VAT rate on residential and transport prices
Sources for key inputs		
International energy price forecasts	AVG*/WB/IMF/EIA/IEA	WB/IMF/EIA/IEA = use institutions' forecasts for oil, gas, and coal AVG = average of above four sources IMF-IEA = average of IEA and IMF Manual = defined in 'Manual inputs' tab
GDP growth forecasts	WEO*/Manual	WEO = growth forecasts from IMF's World Economic Outlook Manual = see 'Manual Inputs' tab

Settings	Defaults (* and ad- di- tional op- tions	Description
Price elas- tic- i- ties of de- mand source	Simple*/Manual	Simple = elasticities drawn from literature review Manual = defined in 'Manual inputs' tab
Income elas- tic- i- ties of de- mand source	Simple*/Manual	Simple = elasticities drawn from literature review Manual = defined in 'Manual inputs' tab
CO2 emis- sions fac- tors	IIASA*/IEA	Use CO2 emissions factors (CO2e per ton of pollutant) from IIASA or IEA.
Fiscal mul- ti- pli- ers	Income- grp*/Estimated/Manual	Income-grp/global = multipliers extracted from macrostructural model and averaged for countries in group/global Estimated = fiscal multipliers estimated econometrically and averaged for regions Manual = user-defined (in 'Manual inputs' tab)

Settings	Defaults (* and ad- di- tional op- tions	Description
Power sector model (elasticity or engineer)?	Average*/Elasticity/Engineering	Engineering = use engineering-type power sector supply model Elasticity = use elasticity-based power sector supply model
Uncertainty adjustments		<p>Base = no adjustment</p> <p>International energy prices adjustment Base*/High/Low = increase forecast prices by 50% Low = reduce forecast prices by 50%</p>
GDP growth adjustment	Base*/High/Low	<p>Base = no adjustment</p> <p>High/Low = increase forecast GDP growth by 50% Low = reduce forecast GDP growth by 50%</p>

Settings	Defaults (* and ad- di- tional op- tions	Description
Price elas- tic- i- ties ad- just- ment	Base*/Vhigh/Low/Vlow	VLow = reduce by 2 standard deviations High = increase by 1 standard deviation VHigh = increase by 2 standard deviations Base = no adjustment
Income elas- tic- i- ties ad- just- ment	Base*/Vhigh/Low/Vlow	VLow = reduce by 2 standard deviations High = increase by 1 standard deviation VHigh = increase by 2 standard deviations Base = no adjustment
Adjust in- come elas- tic- i- ties for GDP lev- els?	Yes*/No	Adjusts income elasticities for electricity, gasoline and diesel with GDP levels (elasticities decrease as countries increase their per capita GDP). The intuition is that, for example, in middle-income countries households purchase fridges, but do not purchase additional fridges as their income increases further.

Settings	Defaults (*) and additional options	Description
Fiscal multipliers adjustment	Base*/High/Low	Base = no adjustment High = increase all fiscal multipliers by 1 standard deviation Low = decrease all fiscal multipliers by 1 standard deviation
Max power sector renewable scaleup rate	Medium*/High/Low	Maximum investment rate for solar and wind per year. High/Low power sector section for the meaning of the options.
Renewable cost decline rate	CtryDefault*/Medium/High/Low/Isde	A learning rate methodology is applied, indicating the percentage of cost reduction of the considered technology arising from every doubling of cumulative installed capacity (experience rate). CtryDefault = 2% increase of the installed capacity and 2.5% for China Low = 1% increase of the installed capacity Medium = 2% increase of the installed capacity High = 3% increase of the installed capacity Vhigh = 4% increase of the installed capacity

Miscellaneous

Settings	Defaults (* and ad- di- tional op- tions	Description
Include en- doge- nous GDP ef- fects?	Yes*/No	Use fiscal multipliers to model effects on GDP, which increases projected energy demand ('rebound effect')
Residential LPG/kerosene al- ways ex- empted	No*/Yes	Exempts LPG/kerosene used in residential sector in all scenarios
National so- cial cost of car- bon (SCC) source	Target*/Ricke2018/ EPA	Shows national social cost of carbon source, which are the 2018 Global US- of climate damages for the country, excluding costs to other countries (real US\$2018 per ton of CO2) Target = global average Paris-consistent carbon price (set to \$75 by 2030) Ricke2018 = uses Ricke et al. 2018 global estimates (further parametrization in 'Advanced options' in mitigation module) Global - US EPA - use global SCC estimate from the US EPA (\$62 in 2018) Manual = see 'Manual inputs' tab

Settings	Defaults (* and ad- di- tional op- tions	Description
Congestion & road dam- age at- tributable to fu- els	0.01	The portion of baseline congestion and road damage externalities attributable to motor fuels
Add non- climate Pigou- vian tax on top?	No*/Yes/FE	Adds additional Pigouvian tax for non-climate externalities (based on costs in baseline years)
Years to phase- in non- climate Pigou- vian tax?	5	Number of years to gradually add non-climate Pigouvian tax on top of main policy

Settings	Defaults (*) and additional options	Description
Add additional excise tax (see 'Manual inputs' tab)?	No*/Yes	Adds manual excise tax, as specified in 'Manual inputs' tab

This table presents the **advanced mitigation options**.

57 Mitigation module (macro & energy effects) --> link to module	
58 <-- Advanced mitigation options	
59 General assumptions	Additional policy-induced efficiency gains pa by sector: Apply existing non-carbon taxes? Energy pricing assumptions
60 First year of model calculations?	2019 Power 0% Coal Yes* Use manual domestic energy prices? No
61 Nominal results in real terms of which year?	2021 Road vehicles 0% Natural gas Yes* Use uniform global assumption for fuel prices (norm) No
62 Use energy balances or (CPAT) energy consumption?	Residential 0% Gasoline Yes* Externalities are part of VAT base for optimal taxes? Yes*
63 Generate Matrix of Energy Consumption Projection?	2019 Industrial 0% Diesel Yes* Producer-side subsidy
64 NDC submission	Latest! Feebates 0% Other oil products Yes* Share of subsidies to phase-out in the policy scenario? 100%
65 Use world (USA) or country-specific discount factor?	World Adjustment to efficiency margins for shadow pricing pol LPG Yes* Apply phaseout in the baseline scenario? Yes
66 Sum all oil products in industrial transformation sector?	Converted Energy efficiency regulations 70% Kerosene Yes* Period to reach full phaseout (baseline scenario)? 5
67 Adjust Annex I country energy-related CO2 EFs to 1.00?	Yes* Vehicle fuel economy 70% Biomass Yes* Share of subsidies to phase-out in the baseline scenario? 100%
68 Adjust non-Annex I country energy-related CO2 EFs to 1.00?	Yes* Residential efficiency regulations 70% Electricity Yes* Consumer-side subsidy
69 Info: adjustment to Efs	1.00 Industrial efficiency regulations 70% Existing carbon tax Share of subsidies to phase-out in the policy scenario? 100%
70 Industrial process emissions scale with industrial CO2 emissions?	Yes* Feebates 100% Apply existing carbon tax (if exists)? Yes* Apply phaseout in the baseline scenario? Yes
71 LULUCF emissions decline at % pa (in absolute value)?	3% Residential Substitution Implicit Efficiencies Assumed existing carbon tax growth per annum (real) 0% Period to reach full phaseout (baseline scenario)? 5
72 Global energy demand scenario	Stations! LPG 56% Existing ETS Share of subsidies to phase-out in baseline 100%
73	Kerosene 45% Apply existing ETS (if exists)? Yes* Price liberalization
74 Social cost of carbon (SCC) assumptions:	Biomass 20% Existing ETS permit price growth per annum (real) 0% Government energy price controls None*
75 Target-consistent carbon price by 2030 (for 'Target' scenario)?	75 NatGas 58% New carbon tax complementary to existing ETS c No* Phase-out price controls in the baseline? Yes
76 NSCC discount rate (p)	2% Price Trajectory New ETS
77 NSCC elasticity of marginal utility (μ)	1.5%* Override dashboard and impose a linear or exponential ETS behavioral responses and revenues adjustment 90%
78 Global social cost of carbon (GSCC) source	Target* If overridden and exponential, what is the real discount rate? 0%
79 SCC (both NSCC and GSCC) - annual rise in real terms?	4%

Figure 3.105: Dashboard: Advanced mitigation options

Settings	Defaults (*) and additional options
General assumptions	

Settings	Defaults (*) and additional options
First year of model calculations?	2019
Nominal results in real terms of which year?	2021
Use energy balances or (CPAT) energy consumption data	Consumption*
Generate Matrix of Energy Consumption Projections for Year	2019
NDC submission	Latest*/First round
Use 'world' (USA) or country-specific discount factors?	World*/Country
Sum all oil products in industrial transformation sector	Converted*/Raw
Adjust Annex I country energy-related CO2 EFs to match UNFCCC GHG inventories?	Yes*/No
Adjust non-Annex I country energy-related CO2 EFs to match CAIT GHG inventories?	Yes*/No
Industrial process emissions scale with industrial CO2 energy emissions?	Yes*/No
LULUCF emissions decline at % pa (in absolute value of start year)?	2.5%
Global energy demand scenario	Stated Policies*/Announced Pledges/Sustainable Development/Net Zero
Social cost of carbon (SCC) assumptions	
Target-consistent carbon price by 2030 (for 'Target' option)	\$75
NSCC discount rate ()	2%*/1%
NSCC elasticity of marginal utility ()	1.5%*/0.7%
Global social cost of carbon (GSCC) source	Target*

Settings	Defaults (*) and additional options
SCC (both NSCC and GSCC) - annual rise in real terms from 2018	0.04
Apply existing non-carbon taxes?	Yes*/No - This setting can be broken down per fuel
Existing carbon tax	
Apply existing carbon tax (if exists)?	Yes*/No
Assumed existing carbon tax growth per annum (real terms)	0
Existing ETS	
Apply existing ETS (if exists)?	Yes*/No
Existing ETS permit price growth per annum (real terms)	0
New carbon tax complementary to existing ETS coverage	No*/Yes
Energy pricing assumptions	
Use manual domestic energy prices?	No*/Yes
Use uniform global assumption for fuel prices (normally 'No')	No*/Yes
Externalities are part of VAT base for optimal taxes?	Yes*/No
Phase out Subsidies	
Producer-side subsidy	
Share of subsidies to phase-out in the policy scenario	100%
Apply phaseout in the baseline scenario?	No*/Yes
Period to reach full phaseout (baseline scenario)	5 years
Share of subsidies to phase-out in the baseline scenario	50%
Consumer-side subsidy	
Share of subsidies to phase-out in the policy scenario	100%
Apply phaseout in the baseline scenario?	No*/Yes
Period to reach full phaseout (baseline scenario)	5 years
Share of subsidies to phase-out in baseline	50%

Settings	Defaults (*) and additional options
Price liberalization	
Government energy price controls	None/Bucketed*/Manual
Phase-out price controls in the baseline?	No*/Yes

This table presents the **advanced power sector options**.

Advanced power sector options			
Elasticity Model Parameters:			
Elasticity model uses economy-wide or sectoral price	Economy-wide	Subsidies	
Use old or new generation costs in elasticity model?	New*	Baseline renewable energy subsidy, \$/kwh nom	\$ -
Use Elasticity Model Power Demand in Engineer Model?	No*	Apply additional RE subsidy to hydroelectric power	No
		Minimum (post subsidy) generation cost \$/kwh real	\$ 0.01
Engineer Model Parameters:			
Dispatch			
k Parameter dispatch	2	Percent allocation of ST storage costs to VRE	100%
Use Spot Fuel Prices in Engineer Power Model	No*	Total hours short term storage for 100% VRE	5
Maximum Coal Capacity Factor	90%	kwh storage to kw interface ratio (hours)	2
Maximum Gas Capacity Factor	90%	Percent allocation of LT storage costs to VRE	33%
Minimum thermal efficiency	10.0%	Starting point of long term storage requirement (%)	75%
Override capacity factor outside of:			
Min (Sol/Wind)	10.0%	GW electrolyzer per Gwyr for 100% VRE (%)	1.0
Min(Others)	1.0%	kWh of LT storage per kW electrolysis	1000
Max(all)	100.0%	Retirement	
		Maximum cost based early coal retirement proportion	80.0%
		Hydro retirement rate set to zero	Yes
PPAs			
Proportion of PPAs in coal and gas Generation	0.0%	Investment	
Phase out any coal and gas PPAs?	Yes*	k Parameter investment	2
Phase out of PPAs begins	2023	WACC: User-, Income- or Tech-dependent?	Income*
Phase out coal and gas PPAs over n years?	5	If User-selected global WACC, what value?	7.5%
		Minimum WACC	1%
Calibration			
Use additional coal intangible cost	Yes*	Max coal/gas invsmnt as a percentage of total gen	5.0%
Manual Value for coal intangible cost (base year)	0	Max hydro/re/nuc/bio invsmnt as a percentage of total gen	2.0%
Manual Value for coal intangible cost (2030)	0	If used, user-defined maximum Wind/Solar Scaleup	2.0%
Use Engineer Covid Adjustment (1=Yes 0=No)	0		

Enable new investments:		WACC override (b/line)		WACC override (policy scenario)		
Coal	New invest? Online as of:	Adjust?	Override	Adjust?	Delta	Override
	If Present* 2019	No*	7%	No*		
Natural gas	If Present* 2019	No*	7%	No*		
Oil	If Present* 2019	No*	7%	No*		
Nuclear	If Present* 2030	No*	7%	No*		
Wind	Yes 2019	No*	7%	No*		
Solar	Yes 2019	No*	7%	No*		
Hydro	If Present* 2030	No*	7%	No*		
Other renewables	If Present* 2030	No*	7%	No*		
Biomass	If Present* 2019	No*	7%	No*		

Solar/wind max invest.		Scale-up limit (MW)		
Gen share add. Limit (%)	CityDefault*	Wind	Solar	
2.0%	2.0%	21.3%	16.4%	
1.0%	1.0%	2.0%	2.0%	
2.0%	2.0%	Limit (MW)	17,412	22,536
3.0%	3.0%	Low	2,658	3,502
4.0%	4.0%	Historical Avg (MW)	4,148	9,204
2.0%	2.0%	High	69,949	50,563
2.0%	2.0%	Capacity	37,505	35,089
2.0%	2.0%	Limit (% tot gen)	32,474	32,474
		Total Generation (GWh)	1,623,690	

Note: Scale up limits are an initial guide. The model will allocate residual needed investment after limits and primary reallocation in proportion to existing capacity. So for example a hydro dominated system will invest in more hydro once the 'allowed' limits are all used up.

Figure 3.106: Dashboard: Advanced power sector options

Settings	Defaults (*) and additional options	Description
Elasticity Model Parameters		

Settings	Defaults (* and ad- di- tional op- tions	Description
k Pa- ram- eter dis- patch	2	Speed of transitioning between generation types with a different cost
k Pa- ram- eter in- vest- ment	2	Speed of transitioning between generation types with a different cost
Hydro re- tire- ment rate set to zero	Yes*/No	
Baseline re- new- able en- ergy sub- sidy, \$/kwh nom	\$0	

Settings	Defaults (* and ad- di- tional op- tions	Description
Apply additional RE subsidy to hydroelectric power?	No*/Yes	
Minimum (post subsidy) generation cost \$/kwh real	\$0.01	
Maximum Coal Capacity Factor	90%	

Settings	Defaults (* and ad- di- tional op- tions	Description
Maximum Gas Capacity Factor Use additional coal intangible cost	90%	Default Yes*: Account for intangible cost of coal. No: Do not account for implicit prices of coal. Manual: User can manually add data.
Manual Value for coal intangible cost (base year)	0	

Settings	Defaults (* and ad- di- tional op- tions	Description
Manual Value for coal intangible cost (2030)	0	
Maximum cost based early coal retirement proportion	80%	
More Engineer Model Parameters		

Settings	Defaults (* and ad- di- tional op- tions	Description
WACC: User- , Income- or Tech- dependent? If User- selected global WACC, what value?	Income*/Tech/Use 7.5%	The WACC can also be technology-dependent, i.e. it can be specified for each technology. The WACC can be defined globally by the user.
Minimum WACC	1%	
Percent allo- ca- tion of ST stor- age costs to VRE	100%	

Settings	Defaults (* and ad- di- tional op- tions	Description
Total hours short term stor- age for 100% VRE kwh stor- age to kw inter- face ratio (hours)	9 hours 2 hours	
Percent allo- ca- tion of LT stor- age costs to VRE	33%	

Settings	Defaults (* and ad- di- tional op- tions	Description
Starting point of long term stor- age re- quire- ment (%VRE)	75%	
GW elec- trolyzer per Gwy/y for 100% VRE (%)	1	
kWh of LT stor- age per kW elec- troly- sis	1000kWh	

Settings	Defaults (* and ad- di- tional op- tions	Description
Use Spot Fuel Prices in Engi- neer Power Model Use	No*/Yes	It uses 5 year centred moving average, where we have data (3y for first year, 4y for second)
Engi- neer Covid Ad- just- ment (1=Yes 0=No)	0	
Max coal/gas in- vsmnt as a per- cent- age of total gen	5%	

Settings	Defaults (* and ad- di- tional op- tions	Description
Max hyd/ore/nuc/bio in- vsmnt as a per- cent- age of total gen	2%	
Max fos- sil/nuclear growth rate	2%	
Engineer: In- vest- ment, Over- rides and Fi- nanc- ing		

Settings	Defaults (* and ad- di- tional op- tions	Description
Plan or en- able new in- vest- ment	If present*/Yes/No/Manual.	If present* = If Nameplate Capacity > 0, then an investment is accounted for in the model, No = Manual. Yes = Planned investments are enabled. No = Disable new investments. Manual = Allows the user to enter data. These data will overwrite the data determined by the model and new capacity will be accounted for as: New Nameplate Investments (MW) = Capacity data entered by the user + planned retirement.
Override Ca- pac- ity Fac- tor		The minimum of capacity factor for solar and wind, as well as for other technologies, and the maximum capacity factor can be modified.
WACC over- ride (base- line and pol- icy sce- nario)		The WACC can be specified for the baseline and the policy scenario.

Settings	Defaults (* and ad- di- tional op- tions	Description
Solar/Wind Max In- vest- ment	Medium*/Low*/High*/None	Percentage of total generation and of existing High/Low/None generation type

3.9.6 Appendix F - Notation in CPAT

This table presents CPAT four key components ('Modules') and their corresponding codes.

- Mitigation module – a reduced form energy model for projecting emissions and estimating impacts of pricing and other mitigation instruments on energy consumption, prices, GHG and local air pollutant emissions, revenues, GDP, and abatement
- Air pollution module – a reduced form air pollution and health model for estimating impacts on premature deaths and disease for local air pollutants like PM2.5 and ozone;
- Distributional module – a cost-push model for estimating impacts of changes in energy prices on industries and households (by income decile and region), including recycling of revenues from mitigation policy.
- Transportation module – a reduced form model for estimating the impacts of motor fuel price changes on congestion and road fatalities.

TabCode	CPAT Module
mit	Mitigation
ap	Air Pollution
dist	Distribution
tra	Transport

3.9.6.1 Sectors

This table displays the sector grouping used in CPAT. It shows the main sectors (industry, power, buildings, transport, other) and the corresponding codes. Each sector breaks into SubSectors, which have their corresponding codes.

SectorGroup	SectorGroupCode	SubSector	SubSectorCode
	ind	cement	cem
industry	ind	construc	cst
industry	ind		foo
industry	ind	food_forest	ftf
industry	ind	nonpowertrans	
industry	ind	ironstl	irn
industry	ind		mac
industry	ind	machinery	mch
industry	ind	mining_chemicals	neu
industry	ind	nonenuse	nfm
industry	ind	nonferrmet	oen
industry	ind	other	omn
industry	ind	other_manufact	
industry	ind	services	srv
industry	ind	worldav	wav
industry	pow	power	pow
power	bld		res
buildings	bld	residential	foo
buildings	bld	food_forest	
buildings	bld	services	srv
buildings	tra		avi
transport	tra	domesair	nav
transport	tra	domesnav	

SectorGroup	SectorGroupCode	SubSector	SubSectorCode
transport	tra	road	rod
other	oth	other	oth
all	all		
eloutput	ele		

3.9.6.2 Fuel types

This table presents the types of fuels used in CPAT and corresponding fuel codes used within CPAT. Additionally, there are three extra expanded fuel codes assigned to the biomass.

Fuel types	FuelCode	Expanded Fuel Code
Biomass	bio	
in which: biodiesel		bgs
in which: biogasoline		bdi
in which: other liquid biofuels		obf
Coal	coa	
Diesel	die	
Electricity	ecy	
Gasoline	gso	
Hydro	hyd	
Jet fuel	jfu	
Kerosene	ker	
LPG	lpg	
Natural gas	nga	
Nuclear	nuc	
Other oil products	oop	
Other renewables / Total self generated renewables	ore	
Renewables	ren	
Solar	sol	
Wind	wnd	

3.9.6.3 Scenarios

This table shows CPAT Scenarios and their corresponding numbers. Baseline, Carbon Tax, and ETS belong to General policies. The remaining scenarios are under Fuel or sector-specific policies.

Policy coverage	Scenario	Number
General policies	Baseline	1
	Carbon tax	2
	ETS	3
Fuel or sector-specific policies	Feebates	4
	Energy efficiency regulations	5
	Coal excise	6
	Road fuel tax	7
	Electricity emissions tax	8
	Power feebate	9
	Electricity excise	10
	Vehicle fuel economy	11
	Residential efficiency regulations	12
	Industrial efficiency regulations	13

3.9.6.4 Sub-models

This table displays sub-models that could be selected for analysis in CPAT.

ModelCode	Model
t	Techoeconomic Model
e	Elasticity Model
b	Both models
a	All

3.9.6.5 Pollutants

This table shows pollutants used in CPAT, their corresponding codes, and additional notes.

Pollutant	Code	Note
Black carbon	bc	
Organic carbon	oc	
Total carbon	tc	bc+oc
Nitrous oxides	nox	
Sulphur dioxide	so2	
Volatile organic compounds (VOC)	voc	
Carbon monoxide	co	
Methane	ch4	
Ammonia	nh3	

3.9.6.6 Unit codes

This table shows the energy units description used across CPAT and their corresponding codes.

UnitCode	Unit Name
twh	Terawatthour
gwh	GigawattHour
ktoe	Thousand (kilo) Tons of Oil Equivalent

3.9.7 Appendix G - Data sources

This table shows the data sources used in CPAT mitigation module.

Particular data set	CPA data e- tags category	Openness	Data source:	Link to data or Terms and Conditions (as applicable)
Greenhouse Gas Emissions	GHGs	Open	UNFCCC & WRI CAIT	WRI CAIT: https://www.wri.org/our-work/project/cait-climate-data-explorer UNFCCC: https://unfccc.int/process-and-meetings/transparency-and-reporting/greenhouse-gas-data/ghg-data-unfccc/ghg-data-from-unfccc
Nationally Determined Commitments	NDCs	Open	Climate Watch	https://www.climatewatchdata.org/explore

Particular data set	CPAT data category	Openness	Data source:	Link to data or Terms and Conditions (as applicable)
Domestic Fuel Prices	dom_prices CPAT (IMF side) derivatives from proprietary data	Open	Various: IEA, Enerdata country offices, OECD. Openly available BNEF climatescope data. Refined.	IEA: https://iea.blob.core.windows.net/3df6-4639-bf60-d73ee8f017c0/IEA-Terms-April-2020.pdf Enerdata: https://www.enerdata.net/terms-conditions.html OECD: https://www.oecd.org/termsandconditions/574055691.1595441182
Elasticities & Annual Efficiency Improvements	Elasticities	Open	Various (literature review)	N/A
Existing Carbon Prices	ECPPOpen	Open	WB Carbon Pricing Dashboard	https://carbonpricingdashboard.wb

Particular data set	CPAT data e-tabs category	Openness	Data source:	Link to data or Terms and Conditions (as applicable)
Power Sector Data	Power	Derivatives from open data	CPAT calculations from EIA data (Electrical Capacity); Energy GP calculation from IRENA (VRE scale-up); General Power Data is an average of openly available sources including: IEA, EIA, IRENA, Bogdanov et al and JRC (EU) Ricke, K., L. Drouet, K. Caldeira and M. Tavoni. "Country-level social cost of carbon" (2018)	N/A
Social Cost of Carbon	SCC	Open	CPAT calculations and projections from multiple data sources	https://www.nature.com/articles/018-0282-y
Energy Consumption	Energy	Consumption	World Development Indicators	https://databank.worldbank.org/development-indicators

Particular data set	CPAT- data e- category	Openness	Data source:	Link to data or Terms and Conditions (as applicable)
Macro data and projections from World Economic Outlook	WEO2020	Open	IMF WEO	https://www.imf.org/en/Publications/economic-outlook-databases#sort=%40imfdate%20d
Macro Balance of Payments from World Economic Outlook	WEO2020	Open	IMF WEO	https://www.imf.org/en/Publications/economic-outlook-databases#sort=%40imfdate%20d
Emissions Factors	EF_GHG	with Permission	IIASA's GAINS model	https://iiasa.ac.at/web/home/rese

Particular data set	CPAT data category	Openness	Data source:	Link to data or Terms and Conditions (as applicable)
	CalVal	Used with Permission	IIASA's GAINS model	https://iiasa.ac.at/web/home/rese
International Energy Price Forecasts	Int_price	Open	World Bank Commodity Price Forecasts, IMF World Economic Outlook, IEA World Energy Outlook	WB: https://www.worldbank.org/en/re markets; IMF: https://www.imf.org/en/Publicati IEA: https://www.iea.org/topics/world-energy-outlook EIA: https://www.eia.gov/outlooks/aec
Population	Popn	Open	Global Burden of Disease (2020); Vollset et al (2020)	https://www.thelancet.com/article/6736(20)30677-2/fulltext
Multipliers	Multipl	Open	CPAT team	N/A

3.9.8 Appendix H – Validation with the EPM model

The following shows more comparisons with the EPM model, using a larger set of countries.

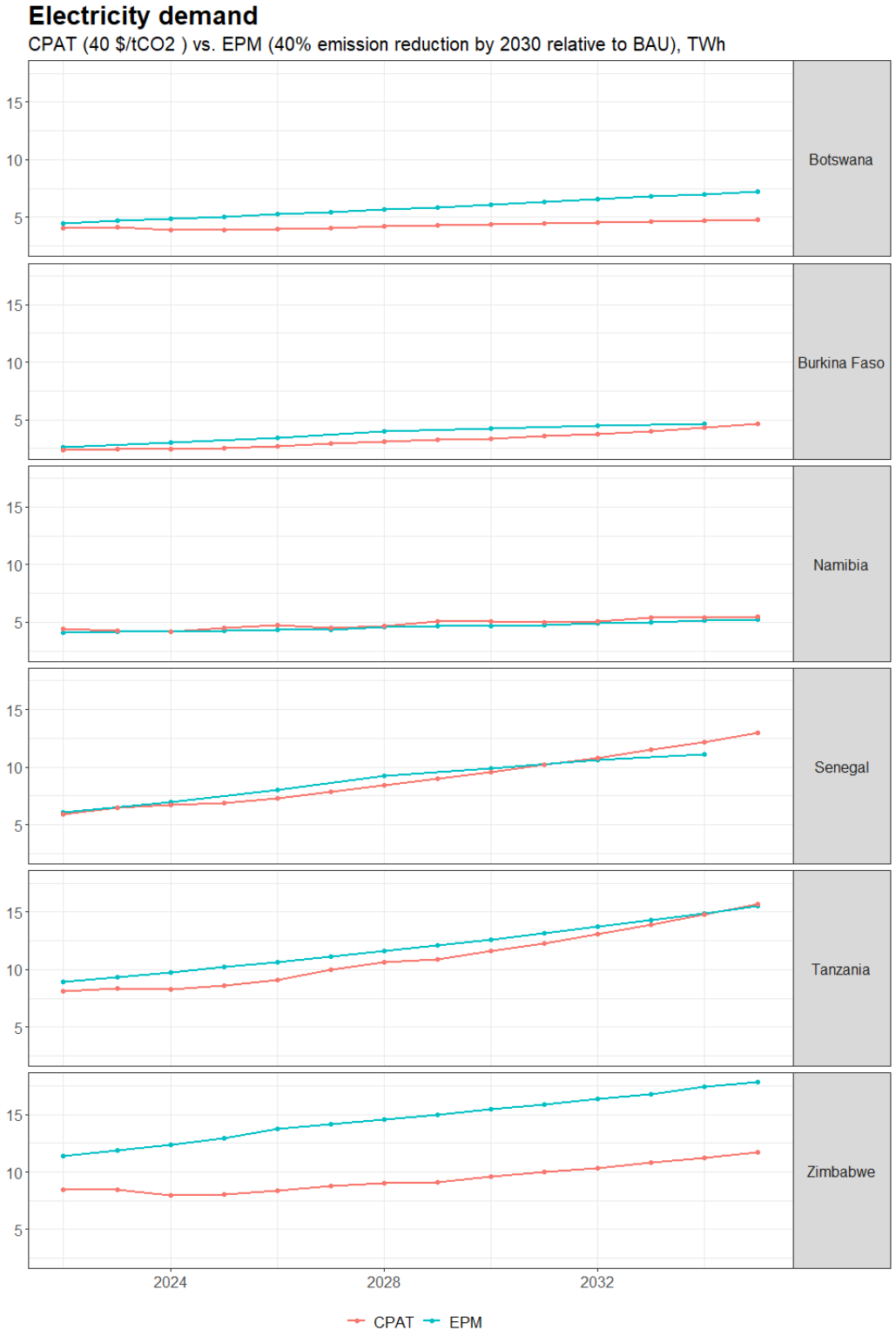


Figure 3.107: Electricity demand Botswana, Burkina Faso, Namibia, Senegal, Tanzania, and Zimbabwe

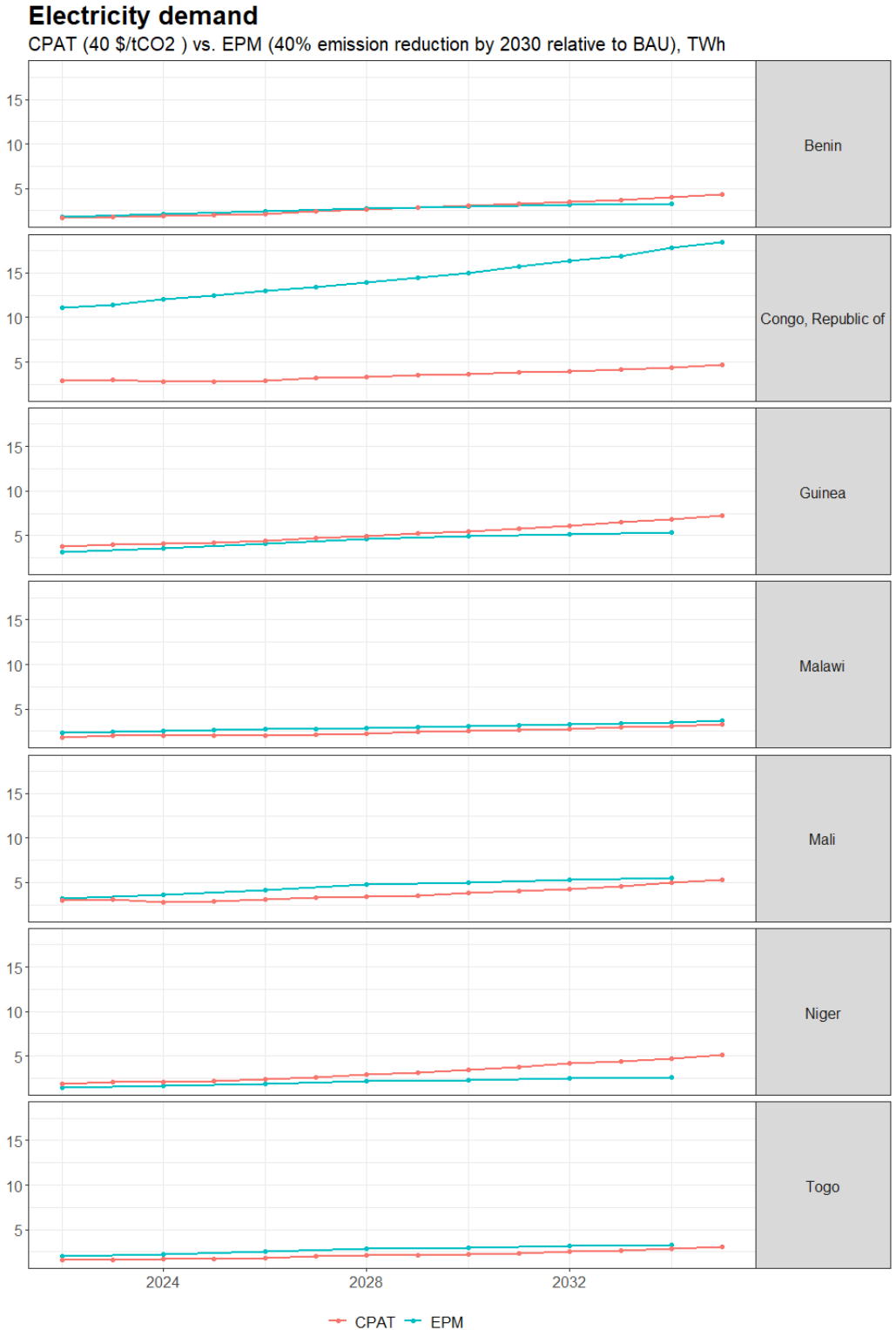


Figure 3.108: Electricity demand Benin, Congo, Guinea, MALawi, Mali, Niger, and Togo

Electricity demand

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), TWh

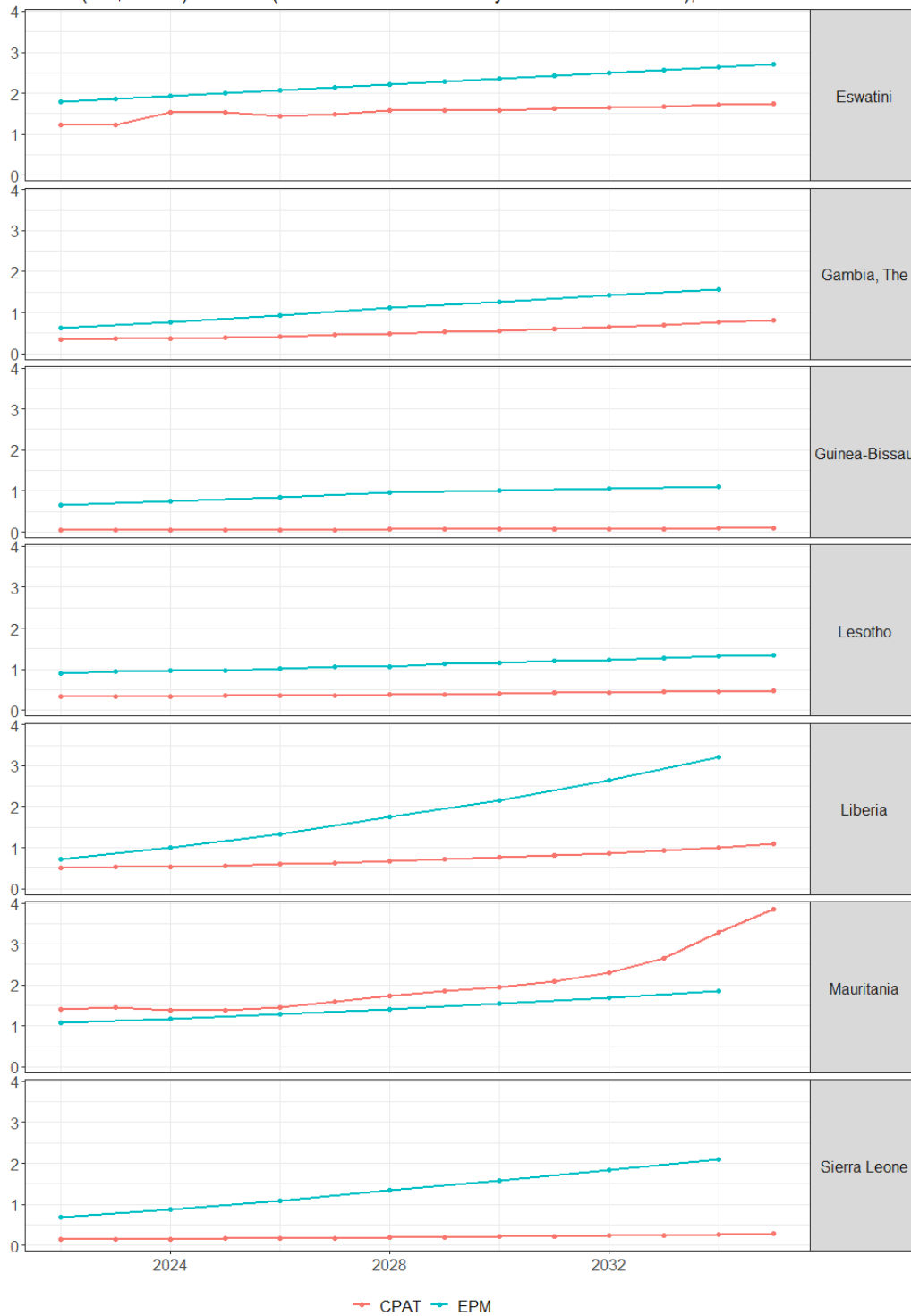


Figure 3.109: Electricity demand Eswatini, Gambia, Guinea-Bissau, Lesotho, Liberia, Mauritania, and Sierra Leone

Electricity generation by fuel type

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), TWh

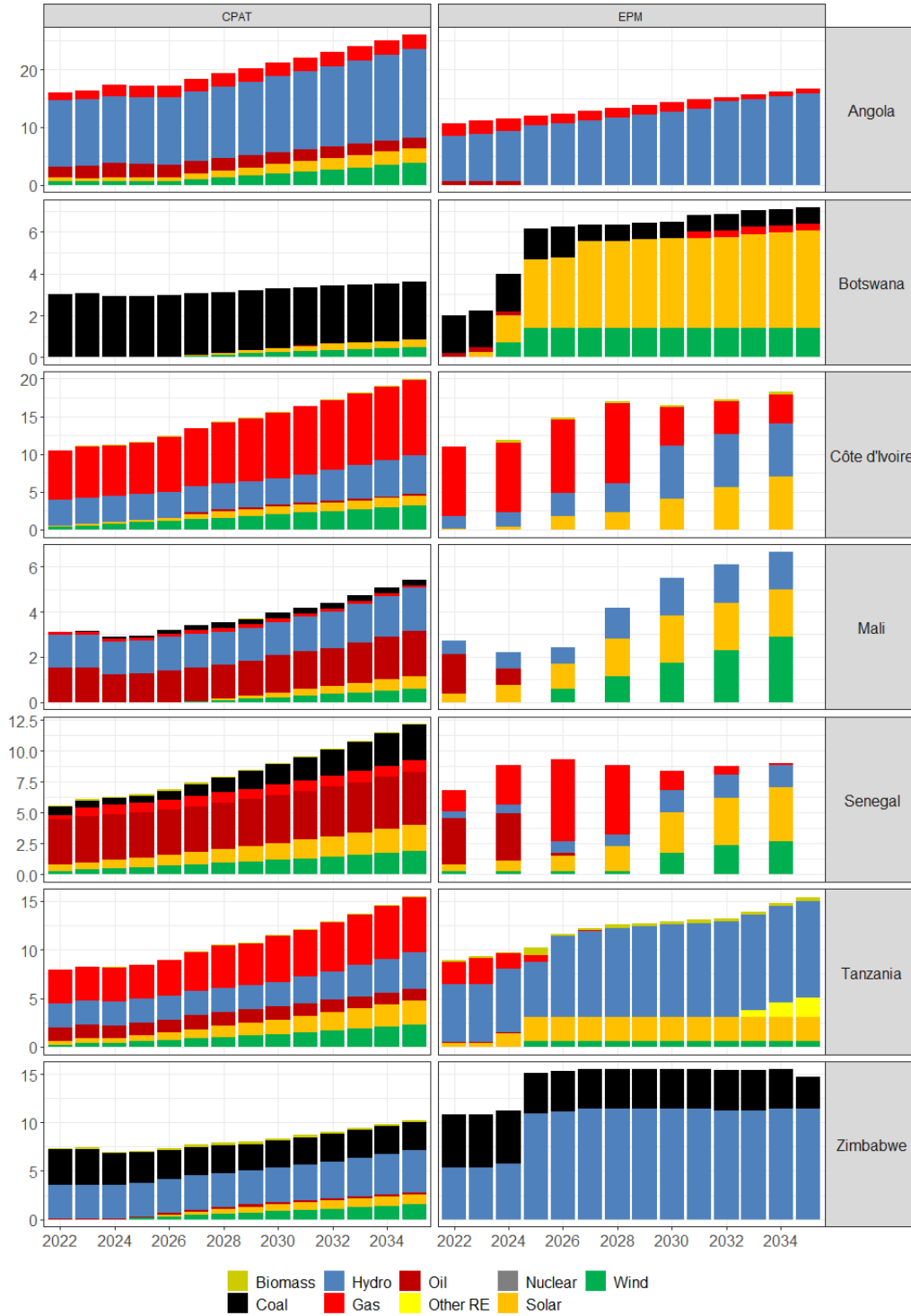


Figure 3.110: Electricity generation by fuel type, Angola, Botswana, Cote d'Ivoire, Mali, Senegal, Tanzania and Zimbabwe

Electricity generation by fuel type

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), TWh

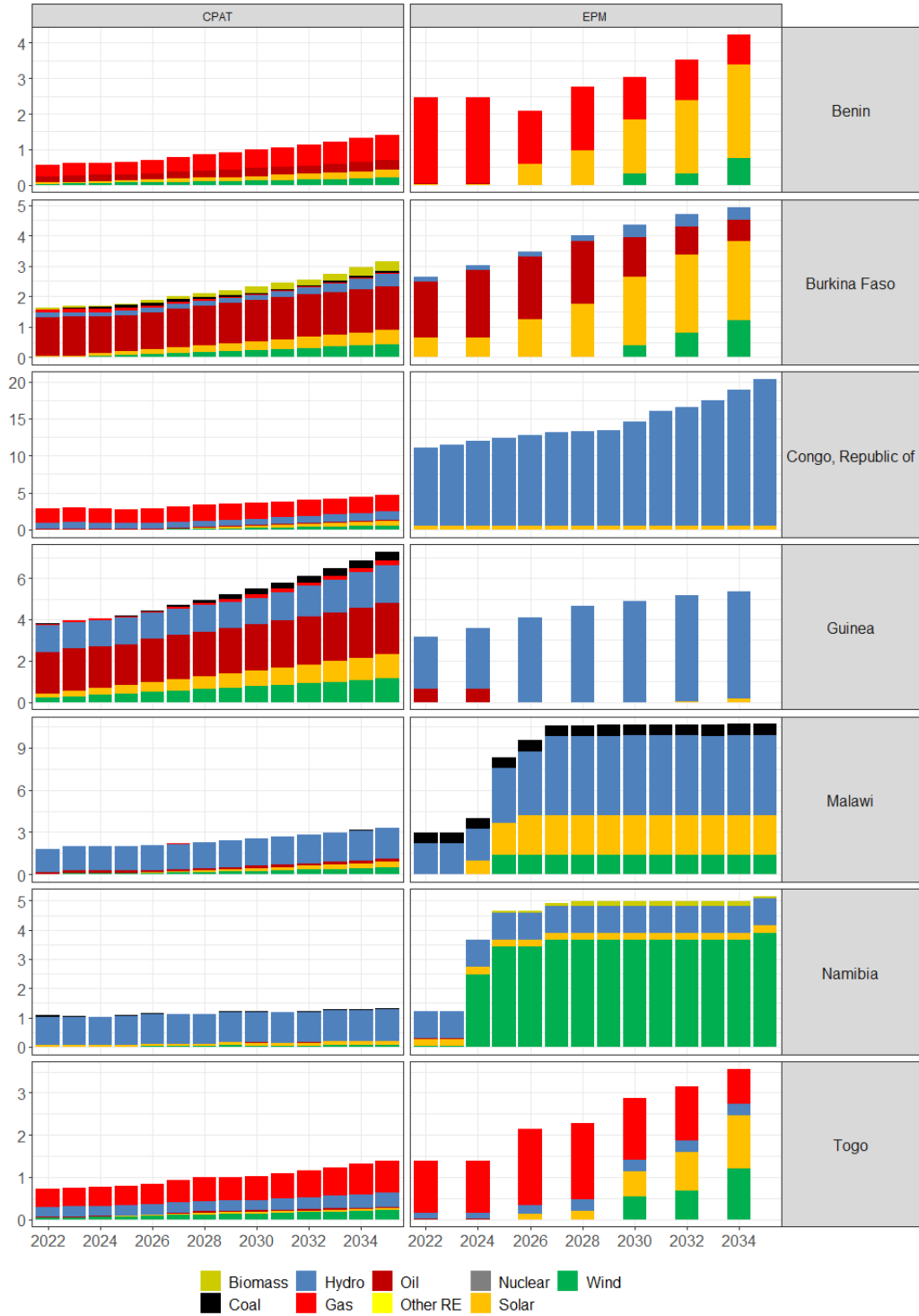


Figure 3.111: Electricity generation by fuel type, Benin, Burkina Faso, Congo, Guinea, Malawi, Namibia, and Togo

Electricity generation by fuel type

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), TWh

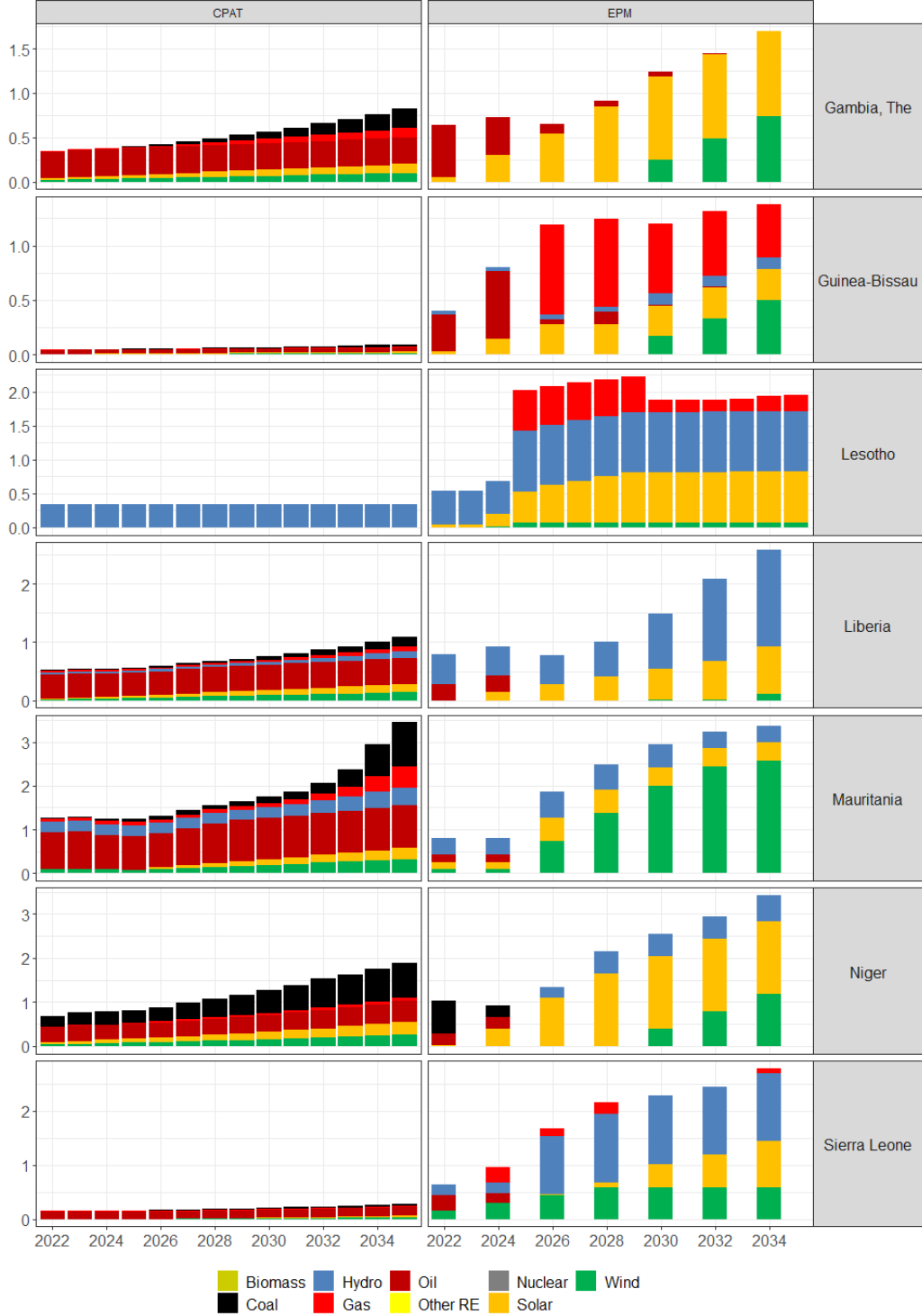


Figure 3.112: Electricity generation by fuel type, Gambia, Guinea-Bissau, Lesotho, Liberia, Mauritania, Niger, and Sierra Leone.

3.9.8.1 Electricity Demand Comparison

3.9.8.2 Electricity Generation By Fuel Type

3.9.8.3 New Investments By Fuel Type

New investments by fuel type

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), GW

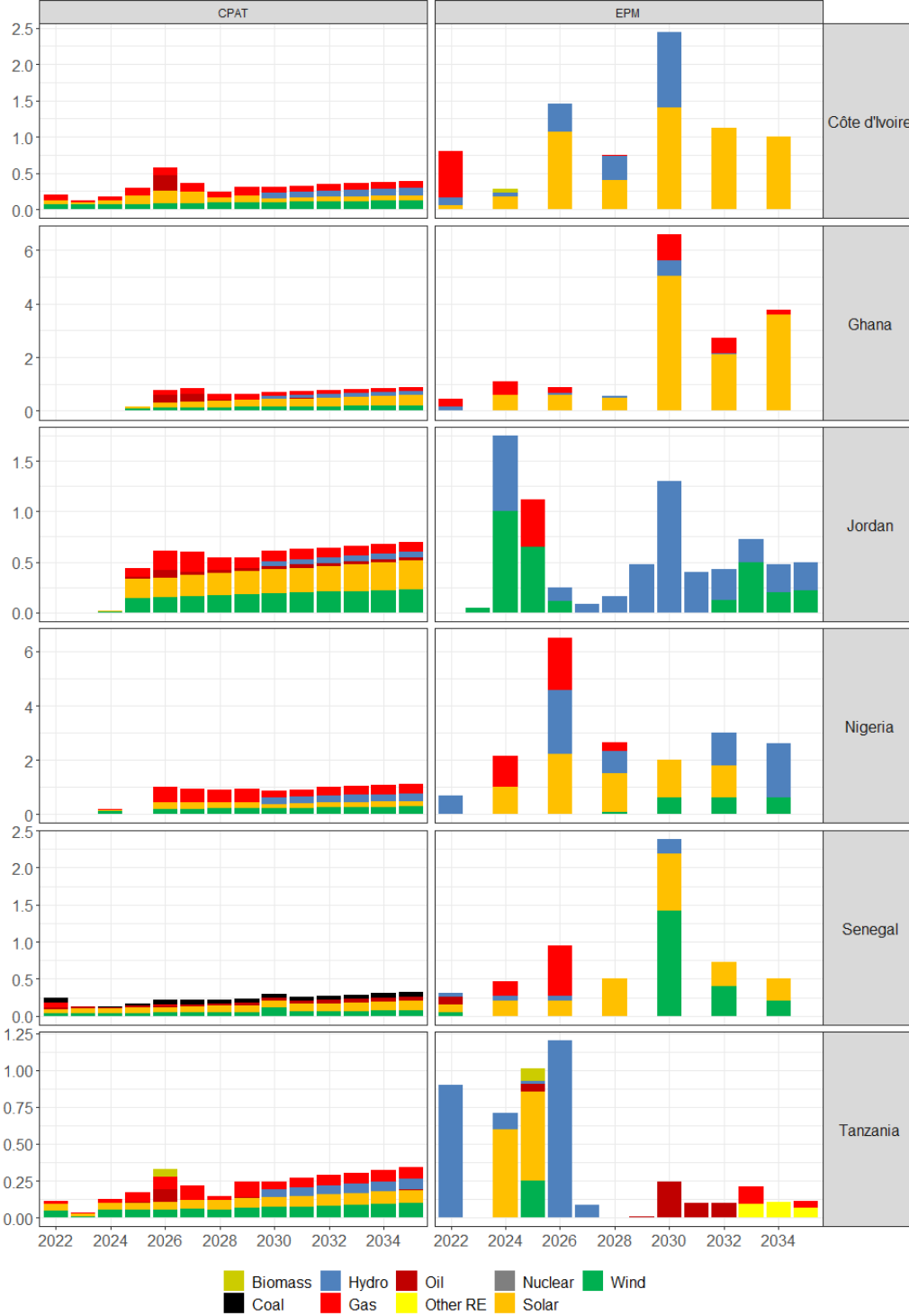


Figure 3.113: New Investments By Fuel Type, Cote d'Ivoire, Ghana, Jordan, Nigeria, Senegal, and Tanzania

New investments by fuel type

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), GW

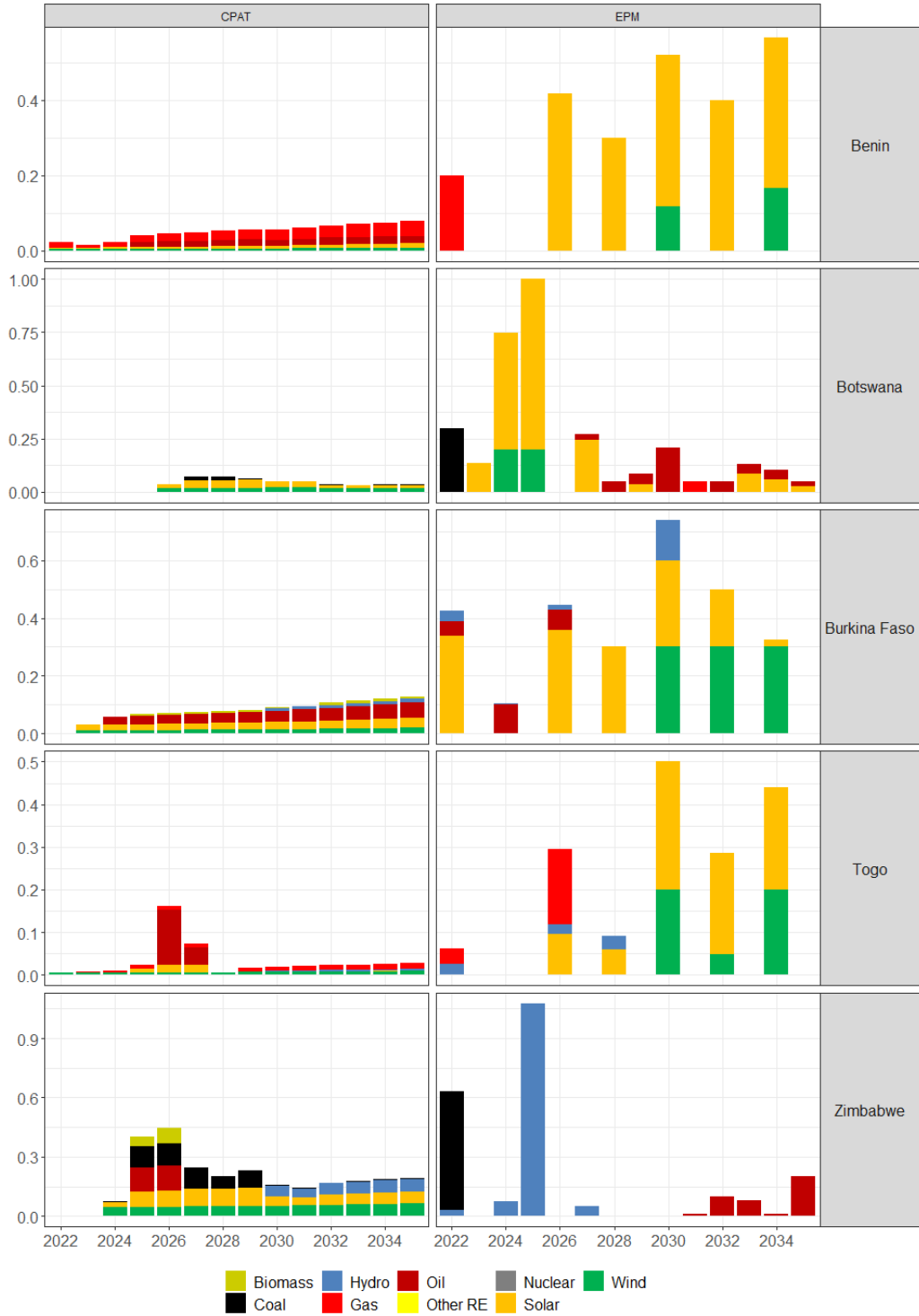


Figure 3.114: New Investments By Fuel Type, Benin, Botswana, Burkina Faso, Togo, and Zimbabwe

New investments by fuel type

CPAT (40 \$/tCO₂) vs. EPM (40% emission reduction by 2030 relative to BAU), GW

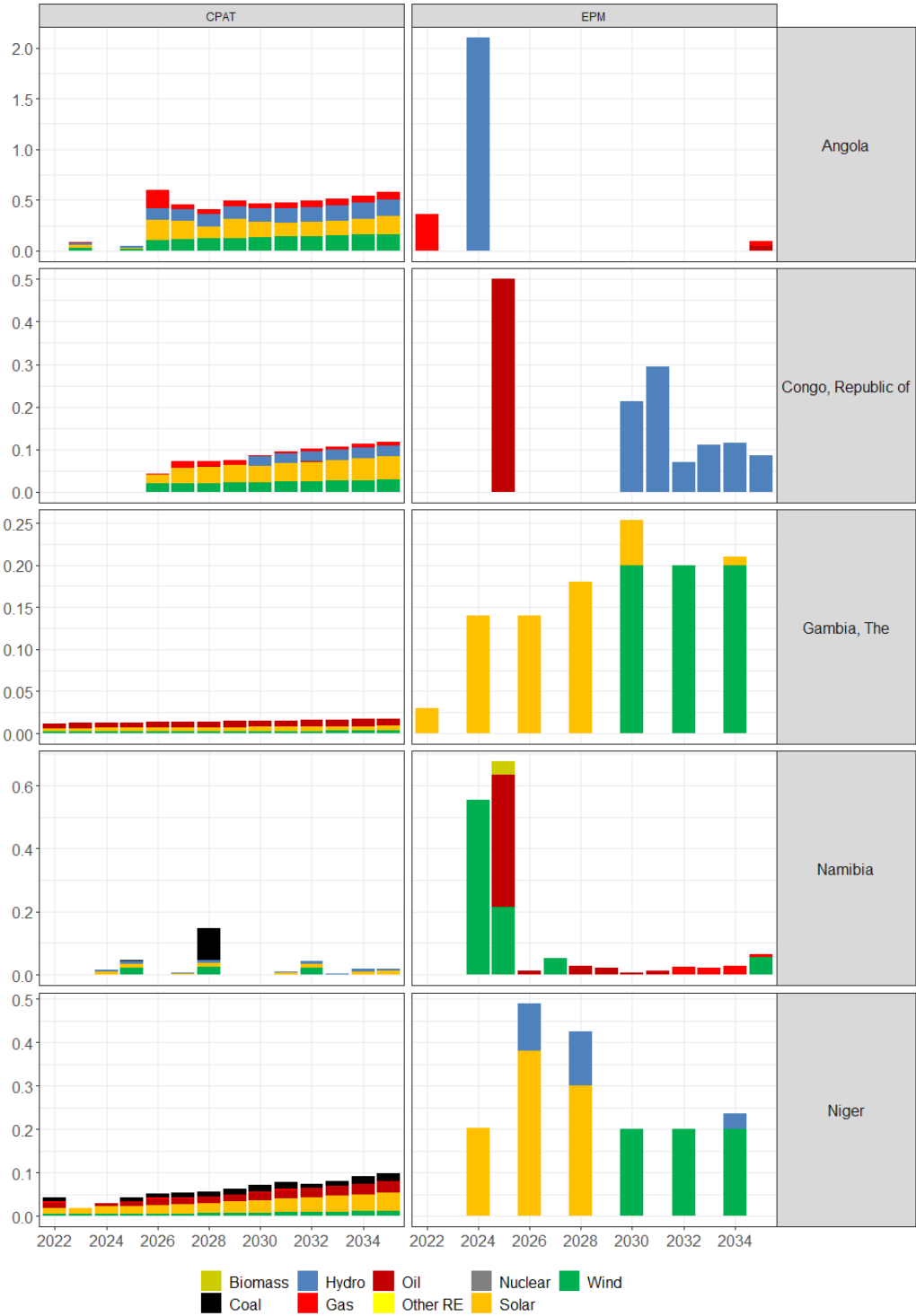


Figure 3.115: New Investments By Fuel Type, Angola, Congo, Gambia, Namibia, and Niger

4 Multipliers

Christian Schoder

cschoder@worldbank.org

Remzi Barış Tercioğlu

rtercioglu@worldbank.org

4.1 List of acronyms

Institutions

OECD Organisation for Economic Co-operation and Development

UNU WIDER World Institute for Development Economics Research

Abbreviations

CPAT Climate Policies Assessment Tool

EET Excise Taxes

EGT Energy Taxes

EVT Total Environmental Taxes

EXT Excise Taxes

GCS Public Consumption

GDP Growth Domestic Product

GIS Public Investment

HIC High-Income Countries

LIC Low-Income Countries

LMIC Lower Middle-Income Countries

MFMod Macro-Fiscal Model

PINE Policy Instruments for the Environment

PIT Personal Income Taxes

TRS Transfers

UMIC Upper Middle-Income Countries

VAT Sales Tax

4.2 Introduction

Carbon pricing has effects on the baseline GDP growth forecasts. For the reference projection of GDP growth, the user can choose between the World Economic Outlook 2020, the World Economic Outlook 2021, and manually entering the growth forecasts. CPAT adjusts these growth forecasts endogenously depending on different carbon pricing and revenue recycling scenarios. Two channels are captured: First, a carbon tax has both direct and indirect effects on GDP. The latter arises when the carbon tax revenues are recycled as a reduction of other taxes and/or as an increase of government spending. These effects are quantified by the fiscal multipliers. Second, the change in GDP affects energy consumption and, therefore, the effective carbon tax revenues. This is captured by the income elasticities of energy demand.

Regarding the first channel, an increase in carbon pricing and the subsequent recycling of the carbon tax revenues into higher government spending and/or lower taxes cause GDP to change with the direction and magnitude depending on the respective spending and tax multipliers. For the fiscal multipliers of energy excise taxes (EET), personal income taxes (PIT), sales taxes (VAT), public investment (GIS), public consumption (GCS), and transfers (TRS), CPAT provides four different sources:

- Income group
- Global
- Manual
- Estimated

Multipliers indicate by how many % GDP responds on impact and in every subsequent year up to a horizon of 10 years to an increase of a fiscal policy instrument by 1% of GDP. The baseline multipliers can be adjusted upwards and downwards by adding/subtracting one empirical standard deviation. This acknowledges the uncertainty around empirical estimates as well as the fact that multipliers tend to be higher during times of economic contraction than expansion. It gives the CPAT user additional flexibility in choosing the appropriate set of multipliers. The present documentation reports the respective methodologies associated with each multiplier source.

When applying fiscal multipliers in CPAT to estimate the GDP effects of a carbon pricing scenario, the following caveats should be noted: First, fiscal multipliers are a link output effects to policy changes in a reduced form. The advantages are that many countries are

covered and that values are comparable between countries. Nevertheless, GDP effects of policy interventions may depend on the state of the business cycle and the design of the policy. These are details which multipliers abstract from. Second, income group and global multipliers are derived from an economic model which is empirically estimated. While the model does not impose a strong prior on the multipliers, there is some small remaining influence of the model assumptions on the multipliers. Moreover, the values are averaged over countries because the country-specific multipliers are very volatile. Finally, the estimated multipliers also need to be interpreted with caution. While they are based on a solid dataset and a state-of-the-art methodology, the dataset only includes 75 countries with more than 10 observations. The results have been averaged over various characteristics (see below for details) and extrapolated to countries which are not covered by the data set. Estimating country-specific multipliers is not feasible given the small number of observations for each country.

4.3 Income group specific multipliers

These multipliers have been extracted from the World Bank's estimated macro-structural model MFMod. Details on MFMod can be found in Burns et al. (2019). The model is estimated for each country and country-specific fiscal multipliers are then computed. To ensure robustness and reduce volatility of multipliers across countries, they are averaged over the countries of an income-group. This leads to four sets of multipliers: One set each for high-income countries (HIC), upper middle-income countries (UMIC), lower middle-income countries (LMIC), and low-income countries (LIC).

MFMod also provides standard errors for these multiplier estimates which are used to adjust the multipliers up- or downwards depending on user preferences.

4.4 Global multipliers

Like above, these multipliers have been extracted from the World Bank's estimated macro-structural model MFMod and are averaged variants of the income group specific multipliers.

4.5 Manual multipliers

The 'Manual input tab' allows the user to enter specific multiplier values for the fiscal instruments mentioned above.

4.6 Estimated multipliers

Estimated multipliers are obtained from a large panel of high-, middle-, and low-income countries.

4.6.1 Methodology for estimating dynamic multipliers using panel data

A thorough discussion of the underlying methodology is provided by Schoder (2022) who exploits the global dataset to study how environmental tax multipliers vary over the business cycle. To obtain dynamic multiplier estimates we employ the local projection method proposed by Jordà (2005) and extended to panel data by Jordà, Schularick, and Taylor (2015) and Jordà, Schularick, and Taylor (2020). As in Dabla-Norris and Lima (2018), we estimate for every horizon $h = 0, 1, \dots, H - 1$,

$$y_{i,t+h} - y_{i,t-1} = \alpha_{i,h} + \delta_{t,h} + \Delta s_{i,t} \beta_h + \Delta x_{i,t} \gamma_h + \epsilon_{t,i,h}$$

where $y_{i,t}$ is the dependent variable. We are interested in explaining 100 times the log of real per-capita GDP in percent. Note that we are estimating cumulative multipliers. Hence, for each horizon we use the change of these variables relative to $t - 1$ as the dependent variable. $s_{i,t}$ is the identified shock variable. For each tax instrument considered, it is the cyclically adjusted tax revenue-GDP ratio in percent. Hence, β_h has the interpretation of a cumulative multiplier. In particular, β_h tells us, under the identifying assumption made and discussed below, by how many percent (age-points) output (employment) increases in $t+h$ relative to $t-1$ if discrete policy increases tax revenues by 1% of GDP. $x_{i,t}$ is a vector of control variables. $\alpha_{i,h}$ and $\delta_{t,h}$ are country and time fixed effects, respectively. To account for heteroskedasticity and autocorrelation we apply the method proposed by Driscoll and Kraay (1998) for estimating a robust covariance matrix of parameters for a panel model. $\epsilon_{t,i,h}$ is the error term.

4.6.2 Data set

To create the data set, we employ various sources: The OECD PINE data set provides revenue data for total environmental taxes (EVT) and energy taxes (EGT). From UNU WIDER, we take data on personal income taxes (PIT), excise taxes (EXT), value added taxes (VAT), government consumption (GCS), transfer payments (TRS), public investment (GIS). Data on GDP, employment, GDP deflator, government spending, and population are taken from the World Bank's World Economic Indicators database. We also use data on total final energy consumption, total final diesel consumption, total final gasoline consumption, diesel and gasoline supply prices, and implicit diesel and gasoline tax rates from a data set compiled to inform CPAT. To remove outliers, we cut off the 1% and 99% percentiles of the changes in the tax revenue-GDP ratios.

4.6.3 Cyclical adjustment of tax revenues and public spending

To address the simultaneous equation bias in the estimates of the tax and spending multipliers which may arise from the feedback of output into tax revenues and spending, we follow the *cyclical adjustment approach* which assumes that there is a given instrument-specific constant output gap elasticity which can be used to remove the cyclical element from the tax revenues. For instance, the tax revenue-GDP ratios $\frac{T}{Y}$ have been cyclically adjusted as

$$\frac{T^*}{Y^*} = \frac{T}{Y} \left(\frac{Y^*}{Y} \right)^{\eta_{YT}-1}$$

where Y^* is trend GDP obtained from the HP filter of log GDP and η_{YT} is the output gap elasticity of the tax revenues. Price, Dang, and Botev (2015) estimated the latter, among other, for PIT, VAT and indirect taxes for OECD countries and Dudine and Jalles (2017) for a large sample of high and low-income countries. For countries without elasticities available, we took the averages as the best guess. Note, that there are no output gap elasticities available for environmental taxes. Hence, for EGT, the output-gap elasticities are estimated following the approach proposed by Price, Dang, and Botev (2015) using total energy consumption as a proxy for the tax base. For the spending instruments, the elasticities have been approximated by the values estimated by Price, Dang, and Botev (2015).

4.6.4 Estimation results

For each tax and spending instrument and for various subsamples, this section presents the estimation results which, in the subsequent section, are used to compute country-specific multipliers. Note that in this section tax multipliers are *not* taken as the negative.

Estimates for the multipliers at horizons larger than eight are restricted to zero when the standard errors become very large, and the sign of the estimate contradicts economic theory. This is to reduce the noise captured by the estimates for larger forecast horizons.

The following tables report the fiscal multipliers from the year of the policy change until 10 years after. The multiplier for each horizon indicates the percentage change of GDP (relative to the year before the policy change) in response to a permanent increase in the policy instrument by 1% of GDP.

4.6.4.1 Pooled panel

GCS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
ABW	0.72	1.06	0.91	0.76	0.58	0.4	0.05	0.03	0.1	0.12	0.09

TRS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
ABW	0.66	0.72	0.63	0.55	0.28	-0.04	-0.28	0	0	0	0

GIS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
ABW	0.47	0.76	0.76	0.52	0.48	0.49	0.16	0.07	0.51	0.55	0.53

PIT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
ABW	-0.19	-0.57	-0.86	-1.26	-0.87	-0.77	-0.73	-0.94	-0.87	-0.71	-0.53

EGT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
ABW	-0.58	-0.76	-1.24	-0.5	-0.37	-0.64	-1.21	-0.77	-0.23	0	0

EVT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
ABW	-0.75	-1.04	-0.84	-0.15	0.17	0	-0.4	-0.03	0.25	0	0

EXT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
ABW	-0.24	-0.35	-0.17	-0.3	-0.26	0.01	-0.18	-0.15	0	0	0

VAT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
ABW	-0.47	-0.62	-0.32	-0.55	-0.83	-0.88	-1.1	-0.9	-0.9	-0.9	-0.9

4.6.5 Income levels

GCS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
HIC & UMIC	0.90	1.24	1.01	0.77	0.39	0.11	-0.26	-0.21	-0.24	-0.27	-0.32
LIC & LMIC	0.44	0.76	0.72	0.73	0.94	0.95	0.67	0.52	0.76	0.86	0.85

TRS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
HIC & UMIC	0.90	1.03	0.86	0.73	0.43	0.10	-0.12	-0.23	-0.34	-0.53	-0.78
LIC & LMIC	0.11	-0.02	0.10	0.12	-0.10	-0.38	-0.68	-0.60	-0.65	-0.89	-1.11

GIS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
HIC & UMIC	0.81	1.22	1.07	0.97	0.78	0.84	0.42	0.23	0.66	0.66	0.49
LIC & LMIC	-0.03	0.06	0.28	-0.15	0.01	-0.10	-0.26	-0.19	0.23	0.36	0.60

PIT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
HIC & UMIC	-0.22	-0.61	-0.90	-1.33	-0.79	-0.63	-0.74	-1.09	-1.07	-0.77	-0.63
LIC & LMIC	0.00	-0.30	-0.62	-0.74	-1.50	-1.79	-0.64	0.31	1.05	-0.04	0.64

EGT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
HIC & UMIC	-0.85	-1.03	-1.24	-0.20	0.28	0.00	-0.83	-0.08	0.93	4.04	5.78
LIC & LMIC	0.23	0.03	-1.22	-1.46	-2.67	-2.87	-2.44	-3.12	-4.27	-3.72	-3.14

EVT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
HIC & UMIC	-1.04	-1.06	-0.72	0.22	0.91	0.76	0.21	0.55	1.46	3.28	4.68
LIC & LMIC	0.47	-0.97	-1.39	-1.72	-3.01	-3.43	-3.03	-2.57	-5.32	-4.47	-3.79

EXT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
HIC & UMIC	-0.28	-0.46	-0.28	-0.33	-0.71	-0.44	0.05	0.22	0.74	1.47	1.91
LIC & LMIC	-0.19	-0.15	0.02	-0.23	0.66	0.95	-0.65	-0.93	-1.48	-1.97	-1.12

VAT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
HIC & UMIC	-0.42	-0.37	-0.02	0.02	0.20	0.05	-0.29	-0.64	-1.12	-1.47	-1.49
LIC & LMIC	-0.58	-1.07	-0.86	-1.62	-2.76	-2.66	-2.65	-2.70	-2.60	-3.13	-3.76

4.6.6 Regions

GCS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Latin America & Caribbean	1.52	1.76	1.35	1.32	1.10	0.94	0.63	0.92	1.42	1.08	0.79
South East Asia & Pacific	0.67	1.08	1.01	1.06	1.11	1.36	0.85	0.78	0.67	1.18	1.04
Africa	0.25	0.29	-	-	-	-	-	-	-	-	-
			0.07	0.50	0.43	1.12	0.94	0.90	0.99	0.54	0.56
Eastern Europe	0.68	1.43	1.30	0.89	0.64	0.40	-	0.16	0.39	0.14	0.16
							0.07				
Central Asia & Middle East	1.58	1.80	1.58	1.77	1.30	0.95	0.48	0.27	0.54	-	0.35
										0.11	
Western Europe & North America	0.32	0.53	0.58	0.24	-	-	-	-	-	-	-
					0.14	0.32	0.69	0.96	1.00	1.09	1.26

TRS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Latin America & Caribbean	0.79	0.92	0.72	0.66	0.56	0.25	-	-	-	-	-
							0.04	0.05	0.18	0.53	0.67
South East Asia & Pacific	0.81	0.97	1.12	1.27	0.83	0.38	0.08	-	-	-	-
								0.44	0.33	0.33	0.23
Africa	0.09	0.00	-	-	-	-	-	-	-	-	-
			0.04	0.35	0.53	0.96	1.26	1.21	1.21	1.55	1.69
Eastern Europe	0.85	0.83	0.58	0.50	0.25	0.15	-	-	-	-	-
							0.08	0.05	0.39	0.50	1.03
Central Asia & Middle East	0.47	0.72	0.92	1.03	1.13	1.08	0.98	1.14	1.27	0.95	0.35
Western Europe & North America	0.70	0.67	0.43	0.00	-	-	-	-	-	-	-
					0.68	1.40	1.64	1.76	1.78	2.05	1.87

GIS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Latin America & Caribbean	0.44	0.60	0.36	0.22	0.06	0.38	0.63	0.25	0.36	0.36	0.81
South East Asia & Pacific	0.35	0.39	0.33	0.14	0.18	0.16	-	-	0.59	1.04	1.07
							0.71	0.48			
Africa	0.13	0.42	0.88	-	-	-	-	-	-	-	-
				0.15	0.15	0.35	0.57	0.28	0.15	0.25	0.36

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Eastern Europe	0.93	1.61	1.40	1.26	1.13	1.23	0.83	0.32	0.40	0.28	- 0.48
Central Asia & Middle East	0.84	1.71	1.73	1.88	1.98	1.71	1.44	0.95	1.53	1.16	1.55
Western Europe & North America	0.43	0.52	0.52	0.63	0.63	0.57	0.53	0.39	0.34	0.32	0.12

PIT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Latin America & Caribbean	1.20	1.43	1.30	- 0.09	- 0.08	- 0.07	- 0.92	- 1.05	- 1.23	- 2.08	- 0.99
South East Asia & Pacific	- 0.69	- 1.05	- 0.76	- 1.55	- 1.48	- 1.68	- 1.78	- 2.06	- 1.95	- 1.91	- 1.01
Africa	-	-	0.08	-	-	-	-	-	-	-	-
Eastern Europe	0.53 0.16	0.40	-	0.32	1.44	1.39	0.66	1.34	0.92	1.35	2.42
Central Asia & Middle East	-	1.65	3.27	4.30	3.67	3.78	4.12	4.24	2.78	1.10	1.82
Western Europe & North America	1.42 - 0.18	3.05 - 0.23	4.38 - 0.33	6.20 0.05	6.64 1.04	6.78 1.34	6.36 1.51	5.23 1.07	5.08 0.79	5.01 0.76	5.59 1.12

EGT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Latin America & Caribbean	0.37	0.53	- 0.58	- 0.43	- 2.44	- 5.66	- 8.87	- 7.66	- 7.57	- 5.90	- 2.52
South East Asia & Pacific	0.46	0.19	- 0.45	- 0.34	0.21	1.01	2.00	0.20	3.51	3.22	6.00
Africa	-	0.29	-	-	-	-	-	-	-	-	1.23
Eastern Europe	0.09 - 0.82	- - 0.86	0.93	1.40	2.41	1.98	1.26	2.11	3.15	0.25	-
Central Asia & Middle East	-	0.59	2.80	4.96	7.35	6.74	6.85	7.85	11.15	13.64	-
Western Europe & North America	1.17 - 2.06	3.98 - 4.91	2.31 - 6.36	3.77 - 7.42	2.51 - 8.73	- - 9.23	- 2.06 8.95	- 3.98 7.28	- 7.78 6.08	- 5.14 3.91	- 4.77 3.83

EVT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Latin America & Caribbean	0.10	0.07	-	-	-	-	-	-	-	-	-
			0.67	0.09	1.45	4.15	6.28	4.81	4.63	3.05	0.54
South East Asia & Pacific	0.95	0.34	-	-	-	-	-	1.09	-	-	-
			0.19	0.56	0.10	0.41	0.15		1.16	0.86	2.39
Africa	-	-	-	-	-	-	-	-	-	-	0.50
	0.45	1.79	1.88	2.90	3.84	3.17	2.70	1.59	3.20	0.94	
Eastern Europe	-	-	-	0.25	2.46	4.57	4.66	4.30	4.71	7.43	10.25
	2.40	2.95	1.95								
Central Asia & Middle East	1.07	2.66	1.63	2.60	2.07	-	-	-	-	-	-
						1.06	2.03	4.23	2.53	2.95	1.58
Western Europe & North America	-	-	-	0.14	0.70	0.55	-	0.53	1.83	2.77	1.96
	0.80	1.04	0.04				0.13				

EXT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Latin America & Caribbean	-	-	-	-	-	-	-	-	-	-	-
	0.38	1.43	2.25	2.60	3.71	4.68	5.55	7.38	7.90	7.45	7.57
South East Asia & Pacific	0.75	0.58	0.94	1.05	0.53	0.72	-	0.50	0.02	0.32	0.49
							0.24				
Africa	0.34	0.13	0.31	-	1.38	1.00	-	-	-	-	-
				0.14			0.08	0.46	0.86	1.08	0.72
Eastern Europe	-	-	0.38	1.01	0.91	2.21	2.58	3.17	3.37	4.74	7.06
	0.82	0.68									
Central Asia & Middle East	0.20	1.03	-	-	-	-	-	-	-	-	-
			0.27	1.70	3.70	3.50	3.08	3.30	3.16	3.80	2.43
Western Europe & North America	-	-	-	-	0.28	0.84	1.34	1.79	2.83	3.32	3.29
	1.06	1.22	0.78	0.67							

VAT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Latin America & Caribbean	0.44	1.03	1.78	2.05	1.71	0.66	0.50	0.76	0.58	-	0.20
										0.34	
South East Asia & Pacific	0.48	0.06	-	-	-	-	-	-	-	-	-
			0.59	0.96	1.39	2.00	1.35	1.14	1.72	2.49	3.01

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Africa	-	-	0.39	-	-	-	-	-	-	-	-
	0.41	0.32		0.41	0.47	0.66	1.35	1.08	1.59	1.09	1.35
Eastern Europe	-	-	-	-	-	-	-	-	-	-	-
	0.78	1.07	0.60	1.00	1.89	1.82	1.97	2.72	2.72	3.56	3.95
Central Asia & Middle East	-	-	-	-	-	-	-	-	-	-	-
	0.97	1.98	3.32	3.53	2.75	0.97	1.21	1.32	2.21	2.86	4.59
Western Europe & North America	-	-	-	0.00	0.10	-	-	-	-	-	-
	0.64	0.64	0.10			0.14	0.51	0.93	1.19	1.28	1.20

4.6.7 Debt levels

GCS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Low debt	0.81	1.14	1.09	0.92	0.53	0.30	0.11	0.10	0.12	0.11	0.08
High debt	0.59	0.92	0.68	0.52	0.61	0.39	-0.02	-0.12	-0.04	0.09	0.21

TRS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Low debt	0.76	0.75	0.68	0.59	0.45	0.28	0.12	0.15	-0.07	-0.18	-0.50
High debt	0.52	0.70	0.57	0.49	0.17	-0.18	-0.54	-0.67	-0.68	-1.08	-1.27

GIS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Low debt	0.74	1.09	0.76	0.57	0.63	0.69	0.43	0.10	0.36	0.37	0.29
High debt	0.18	0.31	0.62	0.29	0.28	0.12	-0.10	-0.05	0.38	0.42	0.54

PIT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Low debt	-0.10	-0.63	-1.00	-1.56	-1.27	-1.12	-1.10	-1.19	-1.02	-0.92	-1.01
High debt	-0.57	-0.44	-0.43	-0.31	0.64	0.69	0.79	0.06	-0.07	0.66	1.84

EGT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Low debt	-0.61	-0.38	-0.52	0.26	0.54	-0.23	-1.06	-0.46	0.41	3.70	5.69
High debt	-0.84	-1.94	-3.11	-2.47	-2.32	-0.68	-0.51	-0.47	-0.40	0.63	0.49

EVT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Low debt	-0.75	-0.56	-0.37	0.48	0.50	-0.18	-0.69	-0.52	0.03	2.45	4.39
High debt	-0.95	-2.45	-2.17	-1.93	-0.49	1.10	0.98	1.74	1.75	2.10	1.46

EXT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Low debt	-0.05	-0.06	0.30	0.16	-0.55	-0.28	-0.18	0.11	0.51	0.95	1.7
High debt	-0.74	-1.13	-1.24	-1.49	-0.03	0.44	-0.10	-0.68	-0.97	-0.78	-0.2

VAT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Low debt	-0.54	-0.81	-0.63	-0.98	-1.35	-1.27	-1.54	-1.86	-2.16	-2.68	-2.86
High debt	-0.53	-0.39	0.37	0.33	0.16	-0.17	-0.23	-0.33	-0.57	-0.83	-1.03

4.6.8 Trade openness

GCS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
High imports	0.79	1.25	1.16	0.99	0.92	1.03	0.83	0.87	0.93	0.87	0.88
Low imports	0.62	0.78	0.54	0.32	-0.03	-0.54	-1.16	-1.24	-1.11	-1.01	-1.02

TRS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
High imports	0.74	0.72	0.69	0.61	0.20	-0.19	-0.42	-0.53	-0.54	-0.63	-1.06
Low imports	0.55	0.69	0.54	0.46	0.32	0.12	-0.13	-0.11	-0.32	-0.65	-0.71

GIS multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
High imports	0.42	0.74	0.61	0.52	0.41	0.33	-0.14	-0.13	0.34	0.39	0.30
Low imports	0.58	0.81	1.07	0.54	0.65	0.78	0.66	0.42	0.82	0.88	0.97

PIT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
High imports	-0.73	-1.66	-2.55	-2.61	-1.70	-1.89	-1.61	-3.13	-3.19	-1.68	-1.98
Low imports	0.04	-0.09	-0.16	-0.67	-0.52	-0.28	-0.35	-0.06	0.03	-0.33	0.00

EGT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
High imports	0.86	0.88	1.20	3.04	5.22	6.43	7.25	8.76	10.49	13.98	15.78
Low imports	-1.09	-1.35	-2.12	-1.81	-2.45	-3.37	-4.58	-4.57	-4.61	-2.58	-0.98

EVT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
High imports	-1.32	-1.56	-0.85	0.81	3.54	4.59	4.96	5.27	5.81	7.63	9.07
Low imports	-0.51	-0.83	-0.84	-0.55	-1.22	-1.94	-2.71	-2.33	-2.21	-0.67	0.66

EXT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
High imports	-0.60	-0.23	0.28	0.20	0.46	0.98	1.70	2.65	2.88	3.81	4.97
Low imports	-0.03	-0.41	-0.43	-0.58	-0.67	-0.54	-1.23	-1.72	-1.53	-1.48	-1.09

VAT multipliers

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
High imports	-0.50	-0.9	-0.66	-1.21	-1.97	-2.02	-2.28	-2.58	-2.66	-3.06	-3.47
Low imports	-0.45	-0.4	-0.05	-0.04	0.05	-0.04	-0.25	-0.48	-0.92	-1.35	-1.49

4.6.9 Computation of country specific dynamic multipliers

In the final step, the raw multipliers for the pooled panel and various subsamples which are reported above are processed to compute country-specific dynamic multipliers for up to 10 years ahead. To obtain country-specific multipliers, we take a weighted average over the respective multipliers from each sample/subsample which the country is part of.

The construction of the weights follows this reasoning: The effective sample size decreases with the length of the estimation horizon. Hence, the longer the multiplier horizon, the more likely the estimate is blurred by noise. This is especially true for the sub-samples as they have fewer observations than the full sample in the first place. To account for this, the weights for the contribution to the multiplier average of the pooled estimates start from zero but increase linearly with the multiplier horizon.

Since, the multipliers for the spending categories (GCS, GIS, TRS) are not very volatile across horizons or across subsamples (especially at short horizons), we assign relatively more weight to the subsamples compared to the panel. The remaining four categories (income levels, region, debt level, trade openness) have equal weights:

Weights for the contribution to the multiplier average of the pooled estimates

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Weights	0	0.083	0.166	0.25	0.333	0.416	0.5	0.583	0.666	0.75	0.833

Weights for the contribution to the multiplier average of the income level, region, debt level or trade openness estimates

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Weights	0.25	0.229	0.208	0.187	0.166	0.145	0.125	0.104	0.083	0.062	0.041

The weights for PIT and VAT multipliers are:

Weights for the contribution to the multiplier average of the pooled estimates

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Weights	0.5	0.541	0.583	0.625	0.666	0.708	0.75	0.791	0.833	0.875	0.916

Weights for the contribution to the multiplier average of the income level, region, debt level or trade openness estimates

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Weights	0.125	0.114	0.104	0.093	0.083	0.072	0.062	0.052	0.041	0.031	0.020

EGT multipliers are very volatile across horizons and subsamples. Hence, we assign a higher weight to the pooled results:

Weights for the contribution to the multiplier average of the pooled estimates

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Weights	0.8	0.816	0.833	0.85	0.866	0.883	0.9	0.916	0.933	0.95	0.966

Weights for the contribution to the multiplier average of the income level, region, debt level or trade openness estimates

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Weights	0.05	0.045	0.041	0.037	0.033	0.029	0.025	0.020	0.016	0.012	0.008

The weights for EVT and EXT multipliers are:

Weights for the contribution to the multiplier average of the pooled estimates

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Weights	0.75	0.771	0.791	0.812	0.833	0.854	0.875	0.895	0.916	0.937	0.958

Weights for the contribution to the multiplier average of the income level, region, debt level or trade openness estimates

Unit	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Weights	0.062	0.057	0.052	0.046	0.041	0.036	0.031	0.026	0.020	0.015	0.010

Finally, the energy excise tax multipliers are approximated by the means of the EGT and EVT multipliers.

4.7 References

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5 Distribution Module

5.1 Introduction

Income inequality, poverty and, more generally, social justice considerations are increasingly becoming a centerpiece of governments' fiscal policy decisions. With the COVID-19 pandemic leading to sharp increases in inequality and poverty, distributional considerations have become even more relevant to decision-makers. In the realm of environmental fiscal reforms, equity and poverty concerns often receive more political attention than in the context of 'traditional' fiscal reforms. Public acceptance is strongly driven by reforms' perceived fairness and impact on low-income households (Klenert et al. (2018); Baranzini et al. (2017)).

The Distribution Module of CPAT1.0 aims to inform the spread of the immediate fiscal incidence *across* (vertical distribution) and *within* (horizontal distribution) income groups, focusing on consumption effects and compensatory schemes. Tax-induced consumer price changes and revenue recycling in the form of direct transfers have been at the center of the literature on fiscal distribution, since such salient, short-term effects are arguably the most relevant from a political economy perspective.¹

The Distribution Module allows the user to estimate the carbon tax incidence on consumption, taking into account the direct effect from the use of fuels, as well as the indirect effect from the consumption of other, non-fuel/-energy goods and services. We follow the standard approach in the literature, combining household budget survey (HBS) information with input-output (IO) data, adjusted such that they yield the same effective carbon price revenues as the ones produced by the Mitigation Module (see Hubacek et al. (2017); Olivier and Ruggeri Laderchi (2018); Vogt-Schilb et al. (2019); Schaffitzel et al. (2020); and Dorband et al. (2019)). Country-fuel-sector- price increases are based on scenario-specific estimates from CPAT's Mitigation Module. Further, the user is provided with two options to relax the typical IO assumptions of full cost-push impacts and absence of behavioral adjustments. Additionally, there is one option to rebate the price increases of a country's primary cooking fossil fuel to selected bottom deciles to help prevent them from switching to biomass. Results from the Distribution Module have been cross-checked and verified against peer-reviewed country case studies (Silva Freitas

¹Note that longer-term structural effects on wages and overall employment may outweigh consumption-side effects as they tend to be positive, larger and progressive (Metcalf (2019b); Markandya et al. 2017). Source-side effects and their distribution (beyond compensation measures) will be considered in version 2.0 of CPAT.

et al. (2016); Farrell (2017); Wier et al. (2005); Jiang and Shao (2014); and stermer2012fuel). See Table 5.5.

Four modes of direct and indirect transfer schemes can be simulated, once the user inputs the share of revenues allocated under each scheme type: i) new or existing targeted transfers (for which the user can decide the targeted percentiles, among other features); ii) transfers towards public investment in infrastructure access; and iii) scaling up an existing social protection scheme (following the targeting of the initial scheme), and iv) reforming countries' personal income tax (PIT) schemes. The revenue amounts available for redistribution are based on scenario-specific estimates from the Mitigation Module. New or existing targeted transfers are universal among the targeted percentiles, while infrastructure transfers are targeted to those households without initial access to clean water, affordable electricity, clean sanitation, Information and Communication Technologies (ICT), or public transport, based on HBS microdata. Revenue recycling that increases current public spending is proportional to the existing social protection schemes, such as social assistance, insurance, or in-kind benefit schemes. Further to the above, transfer scheme targeting is also available for decile-specific population shares that are below international poverty lines (incomes of 1.9 or 3.2 2011 PPP USD/day) via "poverty-conditional cash transfers".

Both negative consumption effects as well as positive compensation scheme effects are expressed as shares of pre-reform consumption and in absolute, per-capita monetary terms on a decile level, separately for the rural, urban, and overall (or national) populations.² For vertical distribution graphs, the user can further choose between decile mean and median consumption data inputs. Horizontal distribution between the 25th and 75th percentile of consumption data inputs within each decile is available for consumption effects (both absent as well as net of compensation schemes).

5.1.1 Summary: Distribution Module Overview

5.1.1.1 Problem definition and approach

Both taxation and spending policies may aim to redistribute in a way that post-tax income equality is ameliorated relative to pre-tax income equality, often with a special emphasis on the poorest segments of the population. Thus, the progressivity or regressivity (that is, the vertical incidence of fiscal policy options across income groups) are policy-relevant considerations. In addition, horizontal distribution (i.e., distribution within the same income group) has gained increasing attention, as the within-income-group spread of the incidence (expressed as a share of consumption) has been found to be potentially larger than the spread of incidence across income groups due to heterogeneous socioeconomic conditions (Fischer and Pizer

²Note that un-adjusted consumption effects should be interpreted as upper-bound estimates in terms of Laspeyres Variation, while positive compensation effects should be interpreted as lower-bound estimates, capturing only the direct monetary benefit, but not the economic co-benefits of, for example, improved health, education, and opportunity.

(2019)). Horizontal distributional policy analysis is of particular interest with respect to political economy as well as poverty considerations. Identifying the parts of the population which will benefit/pay the most, relative to their income, is crucial to designing and evaluating any tax or social assistance scheme.

We measure distributional effects of both tax incidence and revenue recycling in a narrow monetary sense, proxied by relative changes in consumption. Our estimates overstate the negative taxation effects, while understating the positive effects of climate change mitigation and compensation measures. Specifically, the tax incidence analysis focuses on the consumption channel, disregarding structural effects on wages and overall employment, which may positively outweigh consumption-side effects, as they tend to be positive, larger and progressive (Markandya et al. (2016); Metcalf (2019b)). In addition, we disregard the large health co-benefits from improved air and environmental quality as well as reduced traffic accidents, road damage and congestion (please, refer to Technical Appendices of Air Pollution and Transport Modules for further details).

CPAT's proposed compensation schemes can facilitate the reduction of more fundamental inequalities, due to their economic co-benefits of improved health, education, and opportunity. In this sense, proxying compensation scheme benefits to households by using their monetary amounts is an underestimate of said benefits. For example, sustained conditional cash transfer programs to poorer households can significantly improve child health and educational outcomes and, thus, promote the formation of human capital (Cahyadi et al. (2020)). Unconditional cash transfers to the ultra-poor can accelerate the energy transition to cleaner fuels and reduce energy poverty (Aung et al. (2021)). Increasing the quality and quantity of and access to infrastructure has been found to significantly reduce income inequality, poverty and to accelerate growth (Calderon and Servén (2004)). Furthermore, scaled-up social protection measures and access to clean sanitation or clean energy can have similar positive, long-term effects regarding development and human capital outcomes. Finally, improving PIT progressivity has been associated with lower levels of income inequality (Gerber et al. (2020)).

5.1.1.2 Functionalities

CPAT's Distribution Module enables *ex-ante* analyses necessary for informed decision making with respect to how equitable and pro-poor environmental fiscal reform packages would be across countries. As there is no "one-size-fits-all" fiscal reform, the user can choose between several policy design options, particularly with respect to distributional implications within and across household income groups.

The Distribution Module includes the following features:

Tax incidence:

- Consumption effect (from direct and indirect energy consumption)
- Adjustments to consumption effect:

- Mitigation-adjusted tax incidence (“behavioral and structural change”)
- “Emissions-based adjustment of product price changes” (implied revenues on households from IO data consistent with calculated revenues in Mitigation Module)
- Reduced cost pass-through (of energy price increases)
- Behavioral adjustments, considering consumption decile-specific price elasticities of demand
- Special tax rebate for poor households: exemption of cooking fuels

Compensatory scheme incidence:

- Various transfer schemes:
 - Targeted transfers (new or existing social protection scheme(s))
 - Public investment (in infrastructure access spending – e.g., toward SDGs, proxied as cash)
- Current (non-targeted) spending (e.g., scaling up existing social protection scheme(s))Choice of receiving income percentiles and precision of targeting under “Targeted transfers”
- Cash transfers to people below poverty line: targeting of decile-specific population that is below international poverty lines (incomes of 1.9 or 3.2 2011 PPP USD/day)
- Reduction in PIT liabilities

Socioeconomic heterogeneity: results using median/mean HBS decile-level data, across overall, rural and urban (sub-)samples, horizontal/vertical distribution of effects, consumption effects absent (and net of) compensation schemes Some features may not be available for all countries covered, due to data-related availability constraints. The Distribution sheet in CPAT lists the countries available in the Module. .

The full *Guiding Package for CPAT microdata harmonization*, i.e. for preparing a country’s household microdata for inclusion in the Distribution Module, includes a Codebook, supplementary Guidebook, as well as two coding templates (in STATA format) containing data harmonization, preparation and cleaning processes, and can be provided upon request.

5.2 Household budget survey preparation

Estimations of the distribution of carbon tax burdens as well as revenue recycling scheme benefits are largely based on microdata in the form of national household budget surveys (HBSs). This section describes how the primary household-level data are harmonized and aggregated before they are incorporated into CPAT.

5.2.1 Household budget shares

π^{dg} is the budget share of expenditures on a given, category g item by a household in decile d . It represents the consumption as observed in a survey year in a specific country. Household consumption shares are processed from HBSs, which are country-specific and heterogenous in terms of structure and coverage. Where possible, CPAT aims to incorporate the latest HBS of the country. This section describes how these shares are calculated.

First C_j^g , household j 's annual consumption on expenditure category g , is estimated from HBSs. There are two types of expenditure categories: i) direct fuel/energy consumption expenditures: electricity, natural gas, gasoline, diesel, coal, oil/lubricants, LPG, kerosene, charcoal, ethanol and firewood (listed in Figure 5.1) and ii) non-direct fuel/energy consumption expenditure³: appliances, chemicals, clothing, communications, education, food, health services, housing, paper, pharmaceuticals and medicine, recreation and tourism, transportation equipment, public transportation, and other expenditures Table 5.2. Expenditure items in household surveys are mapped to these CPAT expenditure categories⁴ and aggregated to create household consumption under said categories.

In addition to budget shares, CPAT captures households' poverty status with respect to the PPP USD 2011 1.9 and 3.2 daily poverty lines. Dummy variables indicate position with respect to the poverty line(s) based on households' per capita total consumption including actual (not imputed) rent. Poverty incidence is then summed by decile and informs poverty-conditional cash transfers CPAT.

Subsequently, household budget shares π_j^g are calculated for each household j from by dividing each household's consumption of each expenditure category g by total household consumption (C_j). Total consumption (for the purposes of budget share estimation) is the sum of consumption in all expenditure categories g , where the category "housing" (see Table 5.2) does not include imputed rent of a dwelling.⁵

$$\pi_j^g = \frac{C_j^g}{C_j} = \frac{C_j^g}{\sum C_j^g} \quad (5.1)$$

Household budget shares π_j^g are aggregated at the household per-capita consumption decile to arrive at π^{dg} . Household per-capita consumption-based decile generation (as well as any associated percentile statistics) are weighed by the corresponding survey per-capita population weights (*popw*) to ensure sample representativeness at the national level. Household per-capita consumption (*cons_pc*) for the purposes of decile generation is total household consumption including imputed rent (*tot_cons*) divided by household size (*hhsiz*): *cons_pc* =

³Via the consumption of non-energy goods/services that use energy products as inputs into their production process.

⁴Table 5.4 provides a mapping of CPAT non-fuel/energy expenditure categories to GTAP-10 sectors, which is used as a reference for mapping the HBS expenditure items to CPAT expenditure categories.

⁵Rents are imputed in household surveys for households who own their dwelling.

tot_cons/hhsize. Following the literature, CPAT, thus, proxies lifetime income, or standard of living, with consumption expenditures, as they are widely considered a better proxy for welfare than nominal (e.g., wage) income (Deaton (1997)).

π^{dg} is estimated for the overall (i.e., national) sample of households as well as separately for urban and rural households. In addition to average household budget shares, the median, 25th percentile, and 75th percentile statistics are generated for all three samples (overall, urban and rural) at the decile level.

Outlier treatment: Any non-missing consumption shares that lie above three (3) standard deviations (SD) of their corresponding (popw-weighted) means in each specific expenditure category are treated as outliers. The outliers are replaced, by decile, with the decile’s popw-weighted mean household consumption share in the specific expenditure category.

Decile sensitivity check: Household per-capita consumption deciles are based on total household consumption, including imputed rent. The sensitivity of these deciles is checked against the number of households shifting deciles when total household consumption is defined as excluding any rent (*tot_cons_norent in 1*).

5.2.2 Household infrastructure access

In addition to household budget shares, indicators for household access to infrastructure are generated and used within CPAT. di is the weighted share of households (in percent) within decile d which have access to infrastructure category i . These categories are access to i) water; ii) electricity; iii) sanitation; iv) ICT; and v) public transportation (listed and defined in Table 5.3 under “infrastructure access”).

First, ij , a binary variable taking the value of 1 if a household has access to infrastructure category I (0 otherwise), is generated for each household j in the HBS. Next, di , the popw-weighted average share of ij , is calculated for each decile. Note that, since weights are per capita weights, infrastructure access shares represent individuals (not households). Shares are calculated for the overall, urban, and rural sub-samples.

5.3 Microsimulation Method

CPAT’s Distribution Module enables *ex-ante* analysis of distributional effects of user-defined environmental fiscal reform packages, focusing on consumption effects and compensatory schemes (see Figure 5.1 for an overview). Section 5.3.1 outlines the carbon tax incidence analysis, Section 5.3.2 presents further options with regard to tax incidence estimates; Section 5.4 introduces the estimation of compensatory schemes, including transfers and reductions in PIT liabilities.

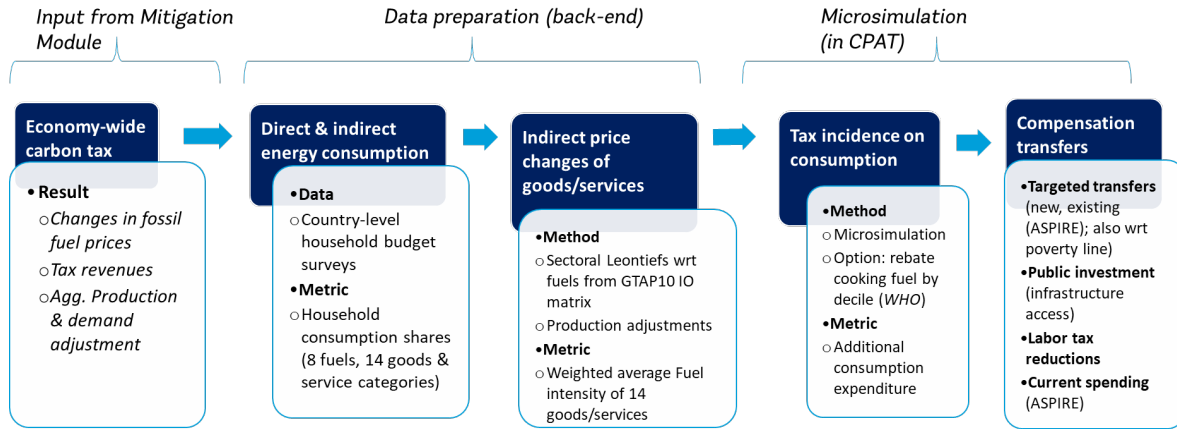


Figure 5.1: Overview of the deployed microsimulation approach and respective functionalities. Note: for the first step (calculating direct and indirect energy consumption), please refer to Section 5.2 Household data preparation.

5.3.1 Tax incidence analysis

CPAT assesses the consumption incidence of carbon fiscal policies across different income groups by means of a microsimulation model. Consumption effects are measured as the costs of maintaining pre-reform consumption (i.e., households' additional expenditures), observed from country-level HBS data, with the user-defined carbon tax scenario in place. Thus, this microsimulation focuses on the short-term consumption changes in terms of compensating variation, assuming fixed consumption patterns. In other words, households are assumed not to adjust their behavior in response to the carbon price, and consumption effects represent upper-bound estimates (Dorband et al 2019). Estimating price and income elasticities of demand, differentiated across countries, income levels and energy/non-energy products is a data- and resource-intensive task, which can be partly integrated into the analysis via a user option to apply decile-specific price elasticities of demand (based on USDA data⁶) to said microsimulation estimates (see also Section 5.3.2).

The **consumer incidence of an energy-based upstream carbon tax** is determined by the tax-induced price changes of fossil fuels, as well as by the direct and indirect energy consumption bundles of households; that is, by households' direct fuel combustion or use of electricity, and the indirect consumption of energy embedded in other goods and services. Thus, the proportion of additional expenditures P of individual j after the policy intervention is a multiplicative function of (i) average energy intensities \bar{e}_{fg} (USD/USD) of fuel f of consumption items from each sector g (note that $f \neq g$); (ii) total expenditures C ; and (iii) the tax rate t for fuel f in sector g , expressed as the price increase post- (p_2) relative to pre-reform (p_1) (USD p_2 /USD p_1) (c.f. endnote 3).

⁶See: <https://data.ers.usda.gov/reports.aspx?ID=17825>

$$p_j = \sum_{fg} p_{fgj} = \frac{\sum_{fg} \bar{e}_{fg} * t_{fg} * C_{gj}}{C_j}, f \in g \quad (5.2)$$

The **tax-induced price changes of fossil fuels** (c.f. Table 5.1 for a list of fuels), which determine households' additional expenditures on direct fuel consumption (for $f=g$, in Equation 5.3), are a function of fuels' carbon intensities, e_f , measured by emissions factors, and pre-existing price distortions in the Mitigation Module. For each user-defined carbon fiscal scenario, price changes are obtained from the Mitigation Module (see respective Mitigation Module Documentation). As price increases vary for each fuel by sector (due to varying emissions factors and baseline pricing), price changes are estimated for each country, year and fuel-sector pair t_{fg} , where "sectors" here are power, industry, and residential. Residential sector fuel price changes are used to calculate the direct consumption effects.

The **tax-induced price changes of goods and services based on the domestic carbon price**, which determine households' additional expenditures on indirect fuel consumption (for $f \neq g$, in Equation 5.3), follow a standard input-output (IO) approach. Consistent with much of the carbon tax literature, all price increases resulting from the user-defined carbon fiscal reform are expected to be fully passed forward, from producers and suppliers to final consumers. Estimated consumer price increases are, thus, absolute upper bounds.⁷ Adapted from basic IO analyses (cf. Leontief (1986); Minx et al. (2009)), household energy intensities \bar{e}_g result as entries of the vector:

$$e_g = f(I - A)^{-1}, f \neq g \quad (5.3)$$

where each fossil fuel sector, f is a vector assigning an energy intensity coefficient to each non-fuel sector. The $(I - A)^{-1}$ matrix, or Leontief inverse (cf. Leontief, 1986), accounts for all upstream inputs that are required to produce one unit of final demand for each sector. I is the identity matrix and A is a normalized matrix of technical coefficients based on inter-sectoral commodity flows.

For **(IO) data**, we use the Global Trade Analysis Project (GTAP-10), (Aguiar et al. (2019)) to compute fossil fuel/energy intensities, and respective price changes for non-fuel sectors. The GTAP-10 database has several advantages. First, it is a consistent global database which harmonizes and scales data for 65 disaggregated sectors (g) and 141 world regions to the year 2014. Such harmonized data improve comparability across country-specific results in CPAT. Important for the estimation of sectoral effects from country-fuel-sector price changes is that GTAP-10 provides a more granular disaggregation of energy sectors than other global IO data with similar regional coverage (e.g., EORA). Yet, while CPAT distinguishes between eight fossil fuel/energy carriers, GTAP-10 includes only five fossil fuel sectors and electricity. Based

⁷Note that CPAT provides the user with an option to approximately estimate how the consumption effects would decrease if the pass-through assumption was relaxed. The approach is explained in Section 5.3.2 and will be refined in subsequent versions of CPAT.

on the concordance table, for GTAP’s “Petroleum and coke products” (p_c) sector, CPAT calculates the weighted average price change, using the economy-wide fuel use volumes of these products (in ktoe from IEA 2020) as weights.

Table 5.1: Concordance table of CPAT fossil fuels (with acronyms) to GTAP-10 fossil fuel sectors

CPAT fossil fuel (f)	GTAP10 sector (f)
Coal (coa)	coa
Electricity (ely)	ely
Natural gas (nga)	gas/gdt
Other oil products (oop)	oil
Gasoline (gso)	
Diesel (die)	
LPG (lpg)	
Kerosene (ker)	p_c

Finally, sectoral energy intensities, e_g , and household expenditures, C_{gj} , are produced for 14 indirect fuel consumption categories. Household consumption is computed as described in Section 5.2 from primary HBS data. Individual consumer items reported in the surveys are mapped to the respective GTAP sectors, which, in turn, are mapped to the 14 consumption categories (c.f. Table 5.1 for concordance between categories and sectors). Thus, all of the 59 non-energy GTAP sectors, which produce end-consumer goods and services, are aggregated into 14 average product categories. Groupings are determined on the grounds of comparable average levels of energy-intensity, as well as to match IEA sectoral definitions used in CPAT. For a complete concordance table among relevant sources of data, please, refer to CPAT’s ‘Mapping’ tab. Thus, for each GTAP fuel sector, f , energy intensities, e_g in Equation 5.3, of the 14 CPAT consumption categories, g , are a weighted average of the energy intensities of the respective non-fuel GTAP sectors, weighted by GTAP’s household final demand vector, Y .

The CPAT Distribution Module is an improvement over the **standard approach in the literature**. CPAT explicitly models a domestic carbon price reform. This means, Leontiefs between fossil fuels and sectors of production reflect only the domestically burned fuels. ‘Embedded’ fuel inputs in imports are not considered in the carbon price-induced price change of goods and services. Particularly in countries with high shares of imports in the goods and services consumed domestically, this approach may yield lower, but more accurate, results on consumption incidence.

5.3.2 Optional features for tax incidence analysis

5.3.2.1 Mitigation-adjusted tax incidence

The Module provides the user with an option to roughly assess how the consumption effects would decrease if emissions reductions induced by the carbon price reform were taken into account. This adjustment scales down overall consumer price increases relative to the scheme's mitigation effect, thus relaxing the cost-push assumption. The Mitigation Module provides estimates of economy-wide GHG emissions reductions and tax revenues from carbon taxation over time. As noted above, the sectorally more disaggregated Distribution Module is based on IO Leontief production functions. This assumes fixed technical coefficients and, thus, full price pass-through, such that the estimated tax incidence is to be understood as an absolute upper bound, or short-term, estimate. CPAT provides the user with an approximate measure of the extent to which consumption effects would decrease if behavioral responses and structural change were accounted for: for the (future) year of interest, CPAT compares the tax revenue estimates of the elasticities-driven Mitigation Module with the tax revenues of the IO-based Distribution Module⁸, i.e. the proportion of revenues raised after and before taking into account behavioral responses:

Let the economy-wide tax burden, or total tax revenues, estimated in the Mitigation Module be P_M^y for year y , and in the Distribution Module be P_D^y ($P_M^y < P_D^y$), where:

$$P_D = \sum_j p_j * C_j \quad (5.4)$$

represents the total revenues expected based on representative HBS consumption data C_j . As survey data aggregates usually do not match national accounts, and as total revenues should compare for the year of interest in the simulation, CPAT scales P_D to match the national accounts in the year of interest y ($2022 \leq y \leq 2030$), such that:

$$P_D^y = P_D * \frac{GDP^y * \theta_c}{\sum C_j} \quad (5.5)$$

where GDP^y represents the expected GDP in the year of interest in the simulation and θ_c represents the final consumption expenditure to GDP ratio for the latest available year from World Bank's World Development Indicators (WDI) database.⁹ Then, the downward adjustment factor to the tax incidence on consumers, p_{Adj} follows as:

$$p_{Adj} = \frac{P_D^y - P_M^y}{P_D^y}, \quad P_M^y < P_D^y \quad (5.6)$$

⁸Please, note that we apply appropriate scaling factors to scale the aggregate microdata from the HBS to match national accounts.

⁹WDI 2020: 'Households and NPISHs final consumption expenditure' (% of GDP; NE.CON.PRVT.ZS)

The adjustment factor p_{Adj} is applied homogenously across the population, represented as a positive relative consumption effect in CPAT. This approach will be refined in subsequent versions of CPAT: estimating with more precision the distributional effects of relaxing the assumption of full pass-through of tax-induced price changes to the end-consumer requires sophisticated data on production- and consumption-side energy price elasticities. Within countries, households of different income strata consume different product bundles (as discussed in the extensive literature on Engel Curves). Thus, for a thorough distributional analysis one needs to determine: a) how price elasticities vary across sectors/products; and b) how price elasticities of demand for products vary with income.

5.3.2.2 Decile-specific price elasticities of demand

CPAT allows the user to model short-term adjustments on the demand side alone, using decile-, country-, and item-specific price elasticities of demand based on (Muhammad et al., 2011). The price elasticities provided are by country and consumption category (COICOP), as well as for high, middle and low income countries. Based on standard concordance tables (ISIC Rev. 4 and CPC 2.1), CPAT maps the elasticities to CPAT consumption categories. CPAT, then, adopts the countries' elasticity reported for the middle deciles and assumes that the upper and lower deciles' elasticities will deviate from the elasticity reported by the same proportion as the elasticities for low- and high-income countries deviate from that of middle-income countries for each consumption item. Following the same approach as in the Mitigation Module, the country-decile-specific price elasticity of demand for consumption category g , ϵ_{use}^g is changing C_j^g as follows:

$$C_j^g * \left(\frac{p_t}{p_{t-1}} \right)^{\epsilon_{use}^g} \quad (5.7)$$

5.3.2.3 Imperfect pass-through

CPAT also provides the user with the option to allow producers to absorb, i.e. not “pass through”, part of the tax-induced price increase. There is ample evidence that (irrespective of any fuel saving/switching behavior) firms pass forward only a portion of the tax-induced energy price increase (Ganapati, Shapiro, and Walker (2020); Abdallah and Le (2020)). The Distribution Module differentiates pass-through coefficients for 14 transport and industrial sectors, with coefficients ranging from 0.7 to 0.9, and averaging 0.8. Coefficients γ_g ($\gamma_g \leq 1$) are applied to the tax rate t for sector g , expressed as the price increase post- relative to pre-reform* ¹⁰, such that the downward-adjusted energy price change t_{ig}^* can be expressed as:

¹⁰Note that this adjustment is carried out in the Distribution Module alone and does not alter revenue estimates in/from the Mitigation Module.

$$t_{fg}^* = t_{fg} * \gamma_g \quad (5.8)$$

5.3.2.4 Emissions-based adjustment of sectoral price changes

As described above, the incidence of goods’ and services’ price changes on consumers is based on GTAP-related fuel-sector Leontiefs. Multiplying the Leontief with the respective fuel’s price change, we obtain ‘indirect’ consumer price changes (in the static option). This multiplication implicitly introduces a price assumption to the GTAP monetary flow of energy: based on observed fuel prices (USD/volume or weight of fuel in 2021), the Mitigation Module estimates expected fuel price changes. Thus, this calculation assumes a corresponding energy flow. However, this energy flow might not necessarily match the observed energy flow by fuel and sector (which CPAT takes from IEA Energy Balances). To correct for this potential imbalance, CPAT allows the user to adjust consumer price incidence by theoretical time-zero revenue flows from the carbon pricing reform modelled. This means that, using the best available empirical data (IEA Energy Balances, GAINS emissions factors, and IMF combined fuel price data), CPAT calculates the revenues that would be raised if no price-induced adjustments were to take place – hence the term time-zero revenues. These theoretical revenue streams are calculated by fuel and CPAT sector. The final demand portion of this price incidence on the economy (usually around 60%, as the remainder is accounted for by goods which are exported or consumed by government and fixed capital formation) is equivalent to the static consumption incidence which should be reflected in the analysis. CPAT, thus, allows the user to scale the baseline incidence to this level. If chosen, additional adjustments are, then, calculated using this new baseline.

5.3.2.5 Cooking-fuel adjusted tax incidence

For selected deciles (starting from the poorest one), CPAT provides the user with the option to exclude from taxation the fossil fuel which is used as a primary cooking fuel. The rationale is as follows: when taxing primary cooking fuels (e.g., LPG), there may be a risk of households being pushed into using traditional, unsustainable biomass (e.g., firewood or charcoal). Therefore, the user can model distributional effects of carbon taxes when households in the bottom (e.g., one or two) deciles do not face an increase in the price of their primary cooking fossil fuel. From a policy design standpoint, this option is to be understood as a rebate. That is, the household will pay the tax when buying the fuel but will receive a compensatory transfer for its cooking needs. Such rebate schemes have received particular attention during India’s LPG subsidy reform, which implemented the Direct Benefit Transfer Scheme for LPG (“Pratyaksha Hataantarit Laabh (PAHAL)”) program.¹¹

¹¹ESMAP (2016) [LPG Subsidy Reform in India | Put the Right Systems in Place First](#). News. Oct 19 2016

Primary cooking fossil fuels are identified for each country based on the World Health Organization (WHO) Household Energy Database¹². Covering 161 countries, the database collects and harmonizes household survey data on the portion of the population cooking with each of fourteen disaggregated fuels, considering surveys between 1970-2014. For each country, and the latest available year of survey data, CPAT determines which of the eight fossil fuels listed in Table 5.1 is most widely used for cooking.

5.4 Incidence of compensatory transfers

Given countries' heterogeneous development status, and political and socioeconomic realities, the design of environmental fiscal reforms varies widely. CPAT provides the user with various options for recycling revenues from environmental fiscal policy scenarios, including via direct and indirect support schemes. Direct transfer schemes to households provide a particularly suitable instrument for increasing public acceptance of tax reforms. This is because they are salient, immediate, and well-targetable. Additionally, direct transfer programs are widely adopted globally, as they have proven to be an effective means of achieving key development goals, with some of them being more administratively simple to implement, due to digitization.

In CPAT, the user can choose among three general options for redistribution via transfers to households. All three redistribution options are modelled as direct, per capita payments averaged by deciles:

1. Decile-targeted transfers (new or existing social protection scheme(s))
2. Public investment (in infrastructure access)
3. Current spending (e.g., scaling up existing social protection scheme(s))
4. Labor tax reforms (as personal income tax reforms)

5.4.1 Targeted and infrastructure-based transfers

Beyond the choice among (a)-c) above), the following four parameters are user-defined:

1. the percentage share of total revenues to be used for (new, existing) targeted and/or public spending transfers;
2. (for new/existing targeted transfers only) the per capita income percentiles to receive the chosen transfer (starting from the bottom of the income distribution; $(C_{jT} \leq p(T)C_j)$);
3. (for new/existing targeted transfers only) the “coverage rate”, i.e. the share of the population targeted actually receiving the transfer; and

¹²See: <https://www.who.int/airpollution/data/household-energy-database/en/>

4. (for new/existing targeted transfers only) the “leakage rate”, i.e. the share of the untargeted population receiving the transfer.

Options 3. and 4. allow the user to consider imperfect implementation of cash transfer schemes, such that parts of the population which would qualify for the transfer do not receive it, while other parts of the population (not qualifying) do so, due to imperfect targeting. Such leakage is assumed to be spread equally across the non-targeted population.

The amount of the targeted, per capita transfer, T , for the targeted population, pop_T , is calculated by dividing total transferred revenues by the total eligible or ‘targeted’ population in the year of interest y , such that:

$$T^y = \frac{P_M^y}{\text{pop}_T^y} \quad (5.9)$$

Where the survey population (i.e., the sum of per capita population weights)¹³ is scaled to match the projected national accounts, pop , based on the IMF’s 2022 World Economic Outlook vintage, for the year of interest, such that:

$$\text{pop}_y^T = \left(\sum \text{popw}_T \right) * \theta_{\text{pop}}^y \quad (5.10)$$

where

$$\theta_{\text{pop}}^y = \frac{\text{pop}^y}{\sum \text{popw}} \quad (5.11)$$

New targeted transfers are conditional on per capita consumption (user-choice 2. above). Thus, the average per capita transfer, T_d^y , for decile d depends on the portion of the decile population, pop_T^{dy} , below the targeted consumption threshold (i.e. for which $C_{jT} \leq p(T)C_j$) such that:

$$T_d^y = T^y * \frac{\sum \text{pop}_T^{\text{dy}}}{\sum \text{pop}^{\text{dy}}} \quad (5.12)$$

Transfers toward infrastructure access are received only by those individuals without initial access to infrastructure type i , i_j (refer to Section 5.2 for details). The user can choose between five different types of infrastructure provision: CPAT defines infrastructure access in line with the WHO’s WASH database¹⁴ and WB WDI database indicators as follows:

¹³Refer to Section 5.2 for a description of the per-capita population weight, $popw$.

¹⁴WHO, UNICEF (2020). WHO / UNICEF Joint Monitoring Programme: Data & estimates. World Health Organization and United Nations Children’s Fund, Geneva and New York. Available from: <https://washdata.org/data>

1. Access to improved water source: piped water on premises (piped household water connection located inside the user’s dwelling, plot or yard), other improved drinking water sources public taps or standpipes, tube wells or boreholes, protected dug wells, protected springs, and rainwater collection
2. Access to improved sanitation facilities: flush/pour flush (to piped sewer system, septic tank, pit latrine), ventilated improved pit (VIP) latrine, pit latrine with slab, and composting toilet
3. Access to electricity: household connection to local/village/national grid/network; not: battery, generator, PV system
4. Access to information & communication technology (ICT): ownership of mobile phone/computer, household internet access
5. Access to public transport

The portion of the decile population, pop_T^{dy} , receiving the transfer, as per Equation 5.12 is calculated based on the weighted share of households in decile d who have access to infrastructure category i , d_i , such that

$$\text{pop}_{Ti}^{\text{dy}} = \sum_{d=1}^{10} \text{pop}^{\text{dy}} * (1 - d_i) \quad (5.13)$$

5.4.2 Transfers through existing social protection schemes

Policy makers may favor extending existing social safety nets for the transfer of carbon tax revenues to households. CPAT, thus, provides the option to proportionally scale up existing social protection schemes, based on the Atlas of Social Protection Indicators of Resilience and Equity (ASPIRE) dataset. For 104 countries, ASPIRE provides quintile-level estimates of per capita transfers received through various benefit schemes, including social assistance measures such as targeted subsidies, in-kind assistance and existing cash transfer programs, labor market protection schemes as well as social insurance (please, refer to the ASPIRE documentation for a full catalog of covered schemes by country¹⁵).

As CPAT simulates a proportional scaling of existing schemes, it first determines the proportion A by which the protection scheme a can be scaled up. Following Equation 5.9 above, CPAT defines:

$$A_a^y = \frac{P_M^y}{A_a^y} \quad (5.14)$$

¹⁵ASPIRE documentation of covered schemes by country: <http://pubdocs.worldbank.org/en/531411485449033265/ASPIRE-expenditure-program-documentation.xlsx>

where A_a^y is the inflation-adjusted total government spending on protection scheme a in the year of interest y . For calculating total government spending, CPAT first multiplies per capita quintile transfer amounts by a fifth of the population popy in the year of interest y , to arrive at total spending by quintile, which is, then, summed up. CPAT arrives at average decile transfers assuming that every two deciles receive the same amount (in per capita terms) as their corresponding quintile (e.g., deciles 1 and 2 receive the per-capita transfer of quintile 1 and so on). The approach described here (in tandem with options 1-4 listed under Section 5.4.1 above) also applies when users choose to recycle carbon tax revenues via existing (as opposed to new) targeted transfers.

5.4.3 Carbon Price Revenue Recycling via Personal Income Tax Reductions

5.4.3.1 Data Requirements and Setup

The distributional effects of carbon price (CP) revenue recycling via personal income tax (PIT) reductions depend on the baseline PIT liabilities of individuals at different segments of the income distribution. Broadly speaking, these liabilities are a function of two components: taxable (i.e., “gross”) income and PIT schedules. To circumvent the modeling of (often complex) PIT systems around the world, CPAT, instead, obtains this information via data on the share of each (disposable, market) income decile’s PIT liabilities in economy-wide PIT liabilities. This information should already account for elements such as, for example, the decile-specific incidence of non-standard PIT regimes, informality, and tax evasion/avoidance, without the need for additional assumptions in this regard.

Decile-specific shares in aggregate PIT liabilities are based on nominal PIT liability data by decile, which is collected from two main sources. First, CPAT relies on the latest vintage(s) of the Luxembourg Income Study (LIS)¹⁶. The LIS contains nationally representative household (HH) survey data on income, demographics and labor market characteristics. Using the LIS, disposable income¹⁷ decile-specific, PIT liabilities are, thus, obtained as the HH-weighted sum of the “hxitax” variable¹⁸. Second, CPAT also obtains similar data from the latest vintage of the Commitment to Equity (CEQ) “Standard Indicators” database¹⁹ for each country. In particular, this database contains information on the incidence (in percent of total market income) of “direct taxes” paid by market income²⁰ decile. From this data, CPAT obtains the

¹⁶See: <https://www.lisdatacenter.org/>.

¹⁷The LIS does not, generally, collect consumption information, making it difficult to obtain income taxes paid by household (weighted) per-capita consumption decile.

¹⁸This variable contains annual “income taxes” paid by households in the survey year and is available for 26 countries (across all World Bank income groups). The surveys mostly date from the period 2010-2019, with the exception of data for the Dominican Republic (2007), Romania (1997) and Sweden (2005).

¹⁹The CEQ “Standard Indicators” database contains data on 42 countries (across all World Bank income groups), based on CEQ analyses covering the period 2009-2017. See: <https://commitmenttoequity.org/indicators.php>

²⁰Similar to the LIS data described above, the CEQ database does not contain data at the consumption decile level.

decile-specific sum of direct taxes paid. Across both data sources, decile-specific shares of income/direct taxes paid are calculated as the ratios of the decile-specific total tax liabilities to the sum of all tax liabilities across deciles.²¹ Taking income/direct taxes as a proxy for PIT liability, the above results in a database of PIT liability shares at the country-year-decile level.²² For the purposes of estimation within the CPAT 1.1. Distribution Module, decile-specific PIT liability shares in economy-wide PIT paid are assumed to be constant over time.

Economy-wide PIT paid is, subsequently, calibrated to equal the product of: i) the average PIT-to-GDP ratio²³ during the period 2010-2019²⁴; and ii) GDP in the year of interest for the distributional effects analysis, y .

Analytically:

$$L_{dcy} = s_{dc} * AVG_PIT_GDP_c * RGDP_{cy} \text{ and } l_{dcy} = L_{dcy}/P_{dcy}$$

where L_{dcy} and l_{dcy} stand for the total and per-capita PIT liabilities of decile d in country c and analysis year y . $AVG_PIT_GDP_{2010-2019}$ is the 2010-2019 average PIT-to-GDP ratio for country c (assumed to be constant over time), $RGDP_{cy}$ is the real GDP in constant 2021 local currency units (LCU) in country c and analysis year y and P_{dcy} is the total population of decile d in country c and analysis year y . P_{dcy} is calibrated to national population in country c and analysis year y , based on the country-specific population distributions obtained from household budget surveys (HBSs) as part of the data requirements for the CPAT consumption incidence calculations. Finally, s_{dcy} is the share of PIT liability of decile d in country c and analysis year y , proxied by data on direct or individual income taxes as described above.

The resulting estimates are merged with each country's, decile-level HBS data for the overall sample²⁵, assuming a 1:1 correspondence between the LIS/disposable income and CEQ/market income deciles and the consumption deciles from the various HBSs. In cases, where LIS and CEQ country coverage overlaps²⁶, CPAT prioritizes the source which covers the latest available

²¹CPAT complements the LIS and CEQ data discussed here with information on PIT paid by household per-capita consumption decile from the household budget surveys discussed above. However, said information is only available for a few countries (Egypt, Pakistan, the Philippines and Ukraine).

²²Any missing country observations are replaced with the mean (or median, should the user choose to report median distributional effects in CPAT) of the country's World Bank income or regional (depending on what the user selects in CPAT) group. See: <https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups>

²³Data on annual, country-level PIT-to-GDP ratios is obtained from the IMF's World Revenue Longitudinal Database (WoRLD). See: <https://data.imf.org/?sk=77413f1d-1525-450a-a23a-47aeed40fe78>.

²⁴The analysis excludes countries with missing 2010-2019 average PIT-to-GDP ratios. Most of these countries (e.g., the Bahamas, Brunei, Oman, Qatar, United Arab Emirates) do not have a PIT regime in place.

²⁵Given the nature of the underlying data and calculations, it was not possible to estimate PIT liabilities by type of sub-sample (e.g., urban vs. rural) and statistic (e.g., median, p25, p75). However, median income/regional group averages will be used for countries that lack decile-specific PIT liability shares, if CPAT users choose to show median distributional effects in CPAT (for all remaining countries median liabilities are assumed to equal mean liabilities).

²⁶This is the case for the following countries: Brazil, Colombia, Dominican Republic, Peru, Russia, South Africa and the United States.

year of data²⁷.

5.4.3.2 Calculations

If the user chooses to recycle a percentage of CP revenues towards “labor tax reductions”, the Distribution Module within CPAT 1.1 estimates resulting per-capita decile-specific gains (in real 2021 LCU) under three (mutually exclusive) PIT liability reduction scenarios:

Targeted Exemption. Under this scenario, selected HH consumption deciles gain the base-line amount of PIT they pay, conditional on available CP revenues. In other words, the allocation of CP revenues would be such that said deciles would not be liable for PIT. In this case, the per-capita LCU gain g for (HH per-capita consumption) decile d in country c and analysis year y can be written as:

$$g_{dcy_TE} = l_{dcy} \mathbb{1}_{[d=exempt]} \mathbb{1}_{[0 \leq \text{remaining CT revenues} \leq l_{dcy}]}$$

where l_{dcy} stands for the per-capita PIT liability of decile d in country c and analysis year y . $\mathbb{1}_{[d=exempt]}$ is an indicator function denoting that decile d has been selected as the decile to be fully exempt from PIT via the use of CP revenues. $\mathbb{1}_{[0 \leq \text{remaining CT revenues} \leq l_{dcy}]}$ is another indicator function denoting that decile d will only benefit from a full PIT exemption of an amount up to (or less than) l_{dcy} , provided that a non-zero amount of CP revenues is available for said purpose. It should, thus, be noted that, even if CP revenues are not enough to fully offset the PIT liability of decile d under this scenario, the Distribution Module will still allocate any remaining CP revenue amounts starting from this decile (and moving upwards onto any remaining deciles), provided that these amounts are available to be allocated.

Personal Allowance. Under this scenario, PIT liabilities are (in absolute terms) uniformly reduced across the PIT-paying population, similar to a per-capita lump-sum transfer to the working population. The respective (equal, per-capita) gains are calculated by dividing the proportion of CP revenues used for PIT reductions by the sum of all individuals in the country. The calculated amount is the maximum available transfer for PIT reduction purposes. Hence, the per-capita LCU gain g for (HH per-capita consumption) decile d in country c and analysis year y can be written as:

$$g_{dcy_PE} = \min\{l_{dcy}, r_{cy}\}$$

²⁷With the exception of the Dominican Republic, CPAT prioritizes LIS over CEQ, due to the former’s coverage of more recent data. LIS is also preferable, owing to its inclusion of data at the disposable income decile level. This is because disposable income-level data is a better proxy for consumption (and, thus, welfare) relative to the market income decile-level data in CEQ. By virtue of this, the LIS deciles are also more comparable to the HBS deciles that CPAT uses when estimating consumption incidence effects.

where l_{dcy} stands for the per-capita PIT liability of decile d in country c and analysis year y . Additionally, r_{cy} is the ratio of all available CT revenues to the sum of all individuals in the country and represents the maximum possible mean per-capita gain of a given decile d . Decile d is, hence, guaranteed l_{dcy} provided that $l_{dcy} < r_{cy}$. Finally, r_{cy} is parametrized such that it reflects use of all CP revenues made available for PIT liability reductions across deciles. Specifically, any remaining revenues following the aforementioned calculations are, once again, equally divided across all individuals in the country and paid out as additional gains under this reform scenario. Since this scenario resembles a lump-sum, per-capita transfer to the working population, gains are likely to be, by default, progressively distributed. This is because transfers tend to represent a larger proportion of poorer households' incomes.

Proportional Compensation. Under this scenario, each (HH consumption) decile receives an average per-capita gain that increases with the HH's baseline PIT liability. In other words, the more PIT a decile pays, the higher the gain. Therefore, the per-capita LCU gain g for (HH per-capita consumption) decile d in country c and analysis year y can be written as:

$$g_{dcy_PC} = l_{dcy} * f_{cy}$$

where l_{dcy} stands for the per-capita PIT liability of decile d in country c and analysis year y . Additionally, f_{cy} is a scalar representing the LCU gain from CP revenue recycling per LCU of baseline PIT paid. This is, in turn, calculated as the total LCU amount of available CP revenues divided by the total LCU amount of PIT paid across all deciles. For instance, a value of 0.5 would be interpreted as each HH consumption decile gaining 0.5 LCUs from CP revenue recycling for each LCU of baseline PIT it pays. In general (depending on the distribution and magnitudes of decile-specific PIT liability shares), this scenario results in a relatively more regressive effect of CP revenue recycling across HH consumption deciles.

5.4.3.3 Assumptions and Caveats

The methodology described here is subject to a series of assumptions and caveats.

- a. The PIT liability calculations assume away any estimates based on actual fiscal regime data (e.g., detailed modeling of tax credits, surtaxes and potential (sector-specific) deductions, etc.). More importantly, no distinction is made in terms of different types of PIT liabilities (e.g., those for self-employed vs. non-self-employed workers). Said distinction could be crucial in determining heterogeneity in the size and dispersion of PIT reduction gains, given that self-employed workers usually face a different PIT schedule.
- b. The PIT liability share calculations also assume that the household survey-type data available via the LIS and CEQ accurately capture the entirety of PIT paid across the income distribution. Ideally, PIT liability calculations would need to draw upon gross income and taxes paid as these are reported in tax return data. However, databases containing such information suffer from sparse country-year coverage and often lack

reporting of decile-specific information.²⁸ On a similar note, the “income taxes” and “direct taxes” variables in the LIS and CEQ databases are assumed to be good proxies for the PIT, which might not be the case given other potential taxes that could be captured therein (e.g., capital gains taxes, etc.).

- c. Any gains from PIT reductions are assumed to be distributed equally across all population sub-groups (i.e., working and non-working individuals, adults and children, men and women, etc.). This is likely to misstate impacts on different deciles to the extent that the demographic composition of population varies substantially across deciles.
- d. The data-generating process outlined above assumes perfect correspondence between consumption and income deciles. The individuals within HH consumption decile 1 (per the HBS data) may not be the same as the ones under income decile 1 (per the LIS and CEQ data). This implies a certain degree of inaccuracy in the use of revenue recycling gains from PIT reductions to offset specific consumer surplus losses from a given CP.
- e. In keeping with the static, partial equilibrium framework of the Distribution Module within CPAT 1.1, the revenue recycling calculations also assume no changes in PIT payments/compliance in response to the CP scenario analyzed in CPAT 1.1. Relatedly, the calculations also abstract from trends in PIT liability patterns, since decile-specific PIT liability shares and PIT-to-GDP ratios are assumed constant over time.
- f. The calculations presented above remain agnostic as to the size and distribution of PIT reduction gains for the urban vs. rural sub-samples in CPAT. To address this issue, CPAT scales any gains by the share of urban and rural population to total population, thus yielding the gains for the urban and rural sub-samples respectively.

Table 5.2: Aggregate and direct fuel consumption expenditure categories

Variable name	Unit	Description
<i>Auxiliary & demographic variables</i>		
hhid	Serial number	Unique household (HH) identifier
iso3	ISO-3 Code	Country ISO-3 code
year	Year (YYYY)	HH interview year
hhsz	Individuals (Count)	Number of members per HH
popw_hh	Weight (Count: HHs)	HH population weight

²⁸For example, see: <https://wid.world/>

popw	Weight (Count: National Population per hhid)	Per-capita population weight (used for binning/deciles); national population represented by each hhid. Calculated as: $hhsz\ast popw_hh$. The sum of popw across all HHs should sum up to the national population in the survey year
urban	Binary Dummy (0,1)	Urban=1 (0) if the HH is in an urban (rural) area
<i>Consumption expenditure aggregates and direct fuel expenditures</i>		
rent_actual	Local Currency Units (LCU)	(Annualized) HH housing rent paid/reported
rent_imputed	LCU	(Annualized) HH unpaid/imputed housing rent (<i>“how much rent would you have paid if you were to pay rent for your home...?”</i>); this should <u>not</u> be included in the “housing” variable (see Guidebook)
rent_total	LCU	(Annualized) HH housing rent paid/reported + unpaid/imputed, calculated as: $rent_actual + rent_imputed$

tot_cons	LCU	(Annualized) HH consumption, calculated as the sum of all consumption expenditures of HH <i>note: this includes paid housing rent AND unpaid/imputed housing rent (“how much rent would you have paid if you were to pay rent for your home”)</i>
tot_cons_acrent	LCU	(Annualized) HH consumption, calculated as the sum of all consumption expenditures of HH (= tot_cons - rent_imputed) <i>note: this excludes unpaid/imputed housing rent (“how much rent would you have paid if you were to pay rent for your home...”)</i>
tot_cons_norent	LCU	(Annualized) HH consumption, calculated as the sum of all consumption expenditures of HH (= tot_cons - rent_actual - rent_imputed) <i>note: this excludes all housing rent</i>
cons_pc	LCU	(Annualized) per-capita consumption, calculated as: tot_cons/hhsize
cons_pc_acrent	LCU	(Annualized) per-capita consumption, calculated as: tot_cons_acrent/hhsize

cons_pc_norent	LCU	(Annualized) per-capita consumption, calculated as: to t
ely	LCU	$\frac{_cons_norent}{hhsiz}$ (Annualized) HH expenditure on electricity (including subscription and connection fees)
gso	LCU	(Annualized) HH expenditure on gasoline
die	LCU	(Annualized) HH expenditure on diesel
ethanol	LCU	(Annualized) HH expenditure on ethanol (if applicable, otherwise leave as=0)
ker	LCU	(Annualized) HH expenditure on kerosene
lpg	LCU	(Annualized) HH expenditure on LPG
nga	LCU	(Annualized) HH expenditure on natural gas
oil	LCU	(Annualized) HH expenditure on (heat) oil, lubricants
coa	LCU	(Annualized) HH expenditure on coal
ccl	LCU	(Annualized) HH expenditure on charcoal
fwd	LCU	(Annualized) HH expenditure on firewood <i>note: imputed <u>and</u> paid</i>

Table 5.3: Infraestructure access variables

wtr_acs	Binary Dummy (0,1)	Access to improved water sources (1=yes; 0=no); World Bank WDI definition: “piped water on premises (piped household water connection located inside the user’s dwelling, plot or yard), other improved drinking water sources public taps or standpipes, tube wells or boreholes, protected dug wells, protected springs, and rainwater collection (excl. non-stationary sources such as packaged or delivered water)”
ely_acs	Binary Dummy (0,1)	Access to electricity (1=yes; 0=no); defined as HH connection to the local/village/national grid/network (excludes battery, generator, PV system; <i>can be approximated by large appliances ownership</i>)
sani_acs	Binary Dummy (0,1)	Access to improved sanitation facilities (1=yes; 0=no); World Bank WDI definition: “flush/pour flush (to piped sewer system, septic tank, pit latrine), ventilated improved pit (VIP) latrine, pit latrine with slab, and composting toilet”
ICT_acs	Binary Dummy (0,1)	Access to Information and Communication Technologies (ICT) (1=yes; 0=no); ownership of mobile phone/computer, HH internet access, etc.
transp_p ub_acs	Binary Dummy (0,1)	Access to public transportation (1=yes; 0=no); (<i>can be approximated by non-zero expenditures on taxis/autobuses, etc.</i>)

Table 5.4: Indirect fuel consumption expenditure categories mapped to GTAP-10 sectors

GTAP10 Sector	GTAP10 Code	GTAP10 Description	CPAT Consumption Categories
40	ele	Manufacture of computer, electronic and optical products	appliances
41	eeq	Manufacture of electrical equipment	appliances
42	ome	Manufacture of machinery and equipment n.e.c.	appliances

GTAP10 Sector	GTAP10 Code	GTAP10 Description	CPAT Consumption Categories
33	chm	Manufacture of chemicals and chemical products	chemicals
35	rpp	Manufacture of rubber and plastics products	chemicals
27	tex	Manufacture of textiles	clothing
28	wap	Manufacture of wearing apparel	clothing
29	lea	Manufacture of leather and related products	clothing
56	cmn	Information and communication	communications
63	edu	Education	education
1	pdr	Rice: seed, paddy (not husked)	food
2	wht	Wheat: seed, other	food
3	gro	Other Grains: maize (corn), sorghum, barley, rye, oats, millets, other cereals	food
4	v_f	Veg & Fruit: vegetables, fruit and nuts, edible roots and tubers, pulses	food
5	osd	Oil Seeds: oil seeds and oleaginous fruit	food
6	c_b	Cane & Beet: sugar crops	food
7	pfb	Fibres crops	food

GTAP10 Sector	GTAP10 Code	GTAP10 Description	CPAT Consumption Categories
8	ocr	Other Crops: stimulant; spice and aromatic crops; forage products; plants and parts of plants used primarily in perfumery, pharmacy, or for insecticidal, fungicidal or similar purposes; beet seeds (excluding sugar beet seeds) and seeds of forage plants; natural rubber in primary forms or in plates, sheets or strip, living plants; cut flowers and flower buds; flower seeds, unmanufactured tobacco; other raw vegetable materials nec	food
9	ctl	Cattle: bovine animals, live, other ruminants, horses and other equines, bovine semen	food

GTAP10 Sector	GTAP10 Code	GTAP10 Description	CPAT Consumption Categories
10	oap	Other Animal Products: swine; poultry; other live animals; eggs of hens or other birds in shell, fresh; reproductive materials of animals; natural honey; snails, fresh, chilled, frozen, dried, salted or in brine, except sea snails; edible products of animal origin n.e.c.; hides, skins and furskins, raw; insect waxes and spermaceti, whether or not refined or coloured	food
11	rmk	Raw milk	food
14	fsh	Fishing: hunting, trapping and game propagation including related service activities, fishing, fish farms; service activities incidental to fishing	food

GTAP10 Sector	GTAP10 Code	GTAP10 Description	CPAT Consumption Categories
19	cmt	Cattle Meat: fresh or chilled; meat of buffalo, fresh or chilled; meat of sheep, fresh or chilled; meat of goat, fresh or chilled; meat of camels and camelids, fresh or chilled; meat of horses and other equines, fresh or chilled; other meat of mammals, fresh or chilled; meat of mammals, frozen; edible offal of mammals, fresh, chilled or frozen	food

GTAP10 Sector	GTAP10 Code	GTAP10 Description	CPAT Consumption Categories
20	omt	Other Meat: meat of pigs, fresh or chilled; meat of rabbits and hares, fresh or chilled; meat of poultry, fresh or chilled; meat of poultry, frozen; edible offal of poultry, fresh, chilled or frozen; other meat and edible offal, fresh, chilled or frozen; preserves and preparations of meat, meat offal or blood; flours, meals and pellets of meat or meat offal, inedible; greaves	food

GTAP10 Sector	GTAP10 Code	GTAP10 Description	CPAT Consumption Categories
21	vol	Vegetable Oils: margarine and similar preparations; cotton linters; oil-cake and other residues resulting from the extraction of vegetable fats or oils; flours and meals of oil seeds or oleaginous fruits, except those of mustard; vegetable waxes, except triglycerides; degreas; residues resulting from the treatment of fatty substances or animal or vegetable waxes; animal fats	food
22	mil	Milk: dairy products	food
23	pcr	Processed Rice: semi- or wholly milled, or husked	food
24	sgr	Sugar and molasses	food

GTAP10 Sector	GTAP10 Code	GTAP10 Description	CPAT Consumption Categories
25	ofd	Other Food: prepared and preserved fish, crustaceans, molluscs and other aquatic invertebrates; prepared and preserved vegetables, pulses and potatoes; prepared and preserved fruits and nuts; wheat and meslin flour; other cereal flours; groats, meal and pellets of wheat and other cereals; other cereal grain products (including corn flakes); other vegetable flours and meals; mixes and doughs for the preparation of bakers' wares; starches and starch products; sugars and sugar syrups n.e.c.; preparations used in animal feeding; lucerne (alfalfa) meal and pellets; bakery products; cocoa, chocolate and sugar confectionery; macaroni, noodles, couscous and similar farinaceous products; food products n.e.c.	food

GTAP10 Sector	GTAP10 Code	GTAP10 Description	CPAT Consumption Categories
26	b_t	Beverages and Tobacco products	food
64	hht	Human health and social work	health_ srv
45	omf	Other M anufacturing: includes furniture	housing
48	wtr	Water supply; sewerage, waste management and remediation activities	housing
49	cns	Construction: building houses factories offices and roads	housing
65	dwe	Dwelling	housing
30	lum	Lumber: manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	paper
31	ppp	Paper & Paper Products: includes printing and reproduction of recorded media	paper
34	bph	Manufacture of pharmaceuticals, medicinal chemical and botanical products	pharma

GTAP10 Sector	GTAP10 Code	GTAP10 Description	CPAT Consumption Categories
51	afs	Accommodation, Food and service activities	rectourism
61	ros	Recreation & Other Services: recreational, cultural and sporting activities, other service activities; private households with employed persons (servants)	rectourism
43	mvh	Manufacture of motor vehicles, trailers and semi-trailers	transp__ eqt
44	otn	Manufacture of other transport equipment	transp__ eqt
50	trd	Wholesale and retail trade; repair of motor vehicles and motorcycles	transp__ eqt
52	otp	Land transport and transport via pipelines	transp__ pub
53	wtp	Water transport	transp__ pub
54	atp	Air transport	transp__ pub
55	whs	Warehousing and support activities	transp__ pub
12	wol	Wool: wool, silk, and other raw animal materials used in textile	clothing
13	frs	Forestry: forestry, logging and related service activities	housing

GTAP10 Sector	GTAP10 Code	GTAP10 Description	CPAT Consumption Categories
18	oxt	Other Mining Extraction (formerly omn): mining of metal ores; other mining and quarrying	appliances
36	nmm	Manufacture of other non-metallic mineral products	housing
37	i_s	Iron & Steel: basic production and casting	housing
38	nfm	Non-Ferrous Metals: production and casting of copper, aluminium, zinc, lead, gold, and silver	appliances
39	fmp	Manufacture of fabricated metal products, except machinery and equipment	appliances
57	ofi	Other Financial Intermediation: includes auxiliary activities but not insurance and pension funding	other
58	ins	Insurance (formerly isr): includes pension funding, except compulsory social security	other
59	rsa	Real estate activities	other

GTAP10 Sector	GTAP10 Code	GTAP10 Description	CPAT Consumption Categories
60	obs	Other Business Services nec	other
62	osg	Other Services (Government): public administration and defense; compulsory social security, activities of membership organizations n.e.c., extra-territorial organizations and bodies	other

Table 5.5: Literature comparison used in the validation of CPAT Distribution Module estimates

Country	Reference source
China	Jiang, Zhujun; Shao, Shuai. 2014. Distributional effects of a carbon tax on Chinese households: A case of Shanghai. Energy Policy, Vol. 13, pp. 269 - 277. DOI: 10.1016/j.enpol.2014.06.005
Costa Rica	Vogt Schlib, et al, 2019. Cash transfers for pro-poor carbon taxes in Latin America and the Caribbean, IDB Working Paper Series, No. IDB-WP-1046, Inter-American Development Bank (IDB), Washington, DC. DOI: https://dx.doi.org/10.18235/0001930

Cyprus	Pashardes et al , 2014. Estimating welfare aspects of changes in energy prices from preference heterogeneity. <i>Energy Economics</i> , Vol. 42, pp. 58-66. DOI: http://dx.doi.org/10.1016/j.eneco.2013.12.002
Denmark	Wier et al, 2005. Are CO2 taxes regressive? Evidence from the Danish experience. <i>Ecology Economics</i> , Vol. 52. pp. 239-251. DOI: 10.1016/j.ecolecon.2004.08.005
Estonia	Poltimae, 2014. U. Tartu PhD Dissertation. The distributional and behavioural effects of Estonian environmental taxes. DOI: N.A
Spain	Sterner, 2012. Distributional effects of taxing transport fuel. <i>Energy Policy</i> , Vol. 41, pp. 75-83. DOI: https://doi.org/10.1016/j.enpol.2010.03.012
France	Sterner, 2012. Distributional effects of taxing transport fuel. <i>Energy Policy</i> , Vol. 41, pp. 75-83. DOI: https://doi.org/10.1016/j.enpol.2010.03.012
Ireland	Farrell, Niall. 2015. What factors drive inequalities in carbon tax incidence? Decomposing socioeconomic inequalities in carbon tax incidence in Ireland. ESRI Working Paper, No. 519, The Economic and Social Research Institute (ESRI), Dublin. DOI: http://aei.pitt.edu/id/eprint/88310
Italy	Sterner, 2012. Distributional effects of taxing transport fuel. <i>Energy Policy</i> , Vol. 41, pp. 75-83. DOI: https://doi.org/10.1016/j.enpol.2010.03.012
Sweden	Sterner, 2012. Distributional effects of taxing transport fuel. <i>Energy Policy</i> , Vol. 41, pp. 75-83. DOI: https://doi.org/10.1016/j.enpol.2010.03.012

Vietnam	Nurdianto, Ditya and Resosudarmo, Budy. 2016. The Economy-wide Impact of a Uniform Carbon Tax in ASEAN. <i>Journal of Southeast Asian Economies</i> Vol. 33, No. 1 (2016), pp. 1–22. DOI: 10.1355/ae33-1a
Brazil	Vogt Schlib, et al, 2019. Cash transfers for pro-poor carbon taxes in Latin America and the Caribbean, IDB Working Paper Series, No. IDB-WP-1046, Inter-American Development Bank (IDB), Washington, DC. DOI: http://dx.doi.org/10.18235/0001930
Canada	Dissou and Siddiqui, 2014. Can carbon taxes be progressive? <i>Energy Economics</i> , Vol. 42, pp. 88-100. DOI: http://dx.doi.org/10.1016/j.eneco.2013.11.010

6 Air pollution module

6.1 Executive summary

Policies aimed to reduce GHG emissions, such as carbon pricing, can lead to a reduction in ambient air pollution, a major health risk¹, due to the co-emission of GHGs and local pollutants when burning fossil fuels. Local pollutants, such as BC, OC, NH₃, SO₂ and NMVOC are responsible for the formation of fine particulate matter (PM_{2.5}) and ozone (O₃) pollution, with known health impacts. CPAT quantifies reductions in mortality and morbidity from improved air quality as part of the co-benefits of carbon pricing.

The air pollution module in CPAT is mostly based on models developed by external institutions and researchers, but also includes modeling developed specifically for CPAT. The main inputs are: (1) energy consumption in time and scenario by fuel type and sector from the Mitigation module, (2) emission factors net of projected average use of pollution control equipment, fuel processing and combustion method from GAINS model², (3) concentrations of PM_{2.5} and ozone for the baseline year, (4) emissions-to-concentrations relationships based on source receptor matrices (TM5-FASST), regression analysis, machine learning models, source apportionment studies and intake fractions, (5) relative risk functions³ for exposure to PM_{2.5} and O₃, and (6) population projections in time.

The main results from the air pollution module are mortality and disability adjusted life-years (DALYs) attributed to air pollution (ambient and household) under the baseline and the carbon price scenario. Other outputs include: (1) the economic valuation of averted deaths (using a transferred value of the statistical life), (2) health expenditure, (3) working days lost due to pollution, and (4) market output losses due to morbidity and mortality.

Reduced-form approximations are used to estimate emissions, concentration of pollutants and health effects. We use and adapt the results of more complex models into simplified relationships. For instance, in the case of the relationship between emissions of pollutants and ambient concentrations of PM_{2.5} and ozone, CPAT includes the option to use the results from a linear

¹Air pollution contributed to 6.67 million deaths and 213 million DALYs in 2019 ([Institute for Health Metrics and Evaluation](#))

²Wagner, Fabian, J Borken-Kleefeld, G Kiesewetter, Z Klimont, W Schoepp, and Marcus Amann. 2020. "Implied Emission Factors in the World Bank's Carbon Pricing Assessment Tool (CPAT)." 2020. <http://dare.iiasa.ac.at/87/>

³Relative risks functions from (GBD 2019 Risk Factors Collaborators 2020)

emulator of a complex global chemical transport model. The results of the air pollution module are in line with other more complex models (see Section 6.8), although both CPAT and the models to which we compare to are subject to uncertainty and the results may be sensitive to the assumptions used. We address this issue in CPAT by allowing the user to input local information, if available, and to switch among methodological options (with the best options possibly dependent on the country chosen).

Caveats in the air pollution module include the use of international databases, the country level (instead of sub national) and annual resolution of the analysis and the uncertainty on estimations. Section 6.9 provides some insights on how the user can tackle these caveats.

6.2 List of Acronyms

Institutions

IHME Institute for Health Metrics and Evaluation

IIASA International Institute for Applied Systems Analysis

ILO International Labour Organization

IMF International Monetary Fund

IPCC The Intergovernmental Panel on Climate Change

OECD Organization for Economic Co-operation and Development

WHO World Health Organization

Abbreviations

BoD Burden of Disease

CPAT Climate Policy Assessment Tool

CLE Current Legislation Scenario

CPI Consumer Price Index

DALY Disability-adjusted life year

EDGAR Emissions Database for Global Atmospheric Research

EF Emission Factor

FASST Fast Scenario Screening Tool

GAINS Greenhouse Gas - Air Pollution Interactions and Synergies

GBD Global Burden of Disease

GDP Gross Domestic Product
GEPR Getting Energy Prices Right
GHED Global Health Expenditure Database, WHO
GTP Global Temperature Potential
GWP Global Warming Potential
HAP Household air pollution
IER Integrated Exposure Response
LPG Liquefied Petroleum Gas
OAP Outdoors air pollution
PAF Population Attributable Fraction
PPP Purchasing Power Parity
PTB Preterm birth
RR Relative Risk
SLCF Short-lived climate forcers
THE Total Health Expenditure
TMREL Theoretical minimum risk exposure level
UNFCCC United Nations Framework Convention on Climate Change
VSL Value of the statistical life
YLL Years of life lost

Pollutants and substances

BC Black Carbon
CH₄ Methane
CO Carbon monoxide
HFCs Hydrofluorocarbons
NF₃ Nitrogen trifluoride
NMVOC Non methanic volatile organic compounds
NO_x Nitrogen oxides
O₃ Ozone
OC Organic Carbon

PFCs Perfluorocarbons

PM2.5 Particulate matter (PM) that have a diameter of less than 2.5 micrometers

POM Primary Organic Matter

SF6 Sulphur hexafluoride

SO2 Sulfur dioxide

Units

6mDMA8h Six-month period with the highest mean, 8-h daily maximum concentration metric

GJ Giga Jules (1 GJ = 10^9 jules)

$\mu\text{g}/\text{m}^3$ Micrograms per cubic meter

ktoe kilotons of oil equivalent

PJ Peta Jules (10^{15} Jules)

ppb parts per billion

6.3 Introduction

The present Chapter focuses on the methodology followed in CPAT to assess the air pollution development co-benefits of carbon pricing.

Figure 6.1 shows an overview of the methodology, where the red box highlights the topics covered in this document. As presented in the figure, the air pollution tab receives as an input the energy consumption for the different sectors and fuels from the Mitigation tab. Emissions (of local and global pollutants) are calculated in the Mitigation tab of CPAT, but the data sources and methodology used is covered in this Chapter. Based on emissions estimates, the Air Pollution tab calculates for each year the concentration of PM2.5 and O3, the health impacts attributed to pollution (deaths and DALYs) and economic impacts of pollution.

The health impacts attributable to air pollution methodology is presented in Figure 6.2. As shown in the figure, the total health burden of pollution is estimated for the baseline scenario and for the carbon price scenario. The impact of the carbon price is then estimated as the difference between the total burden under both scenarios.

The methodological steps presented in Figure 6.1 and Figure 6.2 are described in the following sections. Section 6.4 presents the sources and methods for estimating emissions. Section 6.5 explains the relationship between emissions and ambient pollution. Section 6.6 introduces the quantification of the health burden of air pollution and Section 6.7 presents the quantification of the economic impacts of pollution. This Chapter presents additional sections to validate

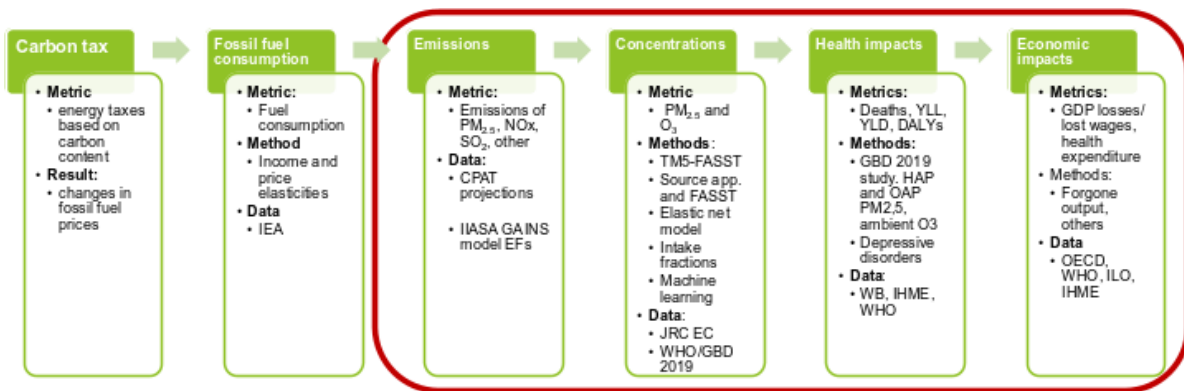


Figure 6.1: Overview of CPAT methodology

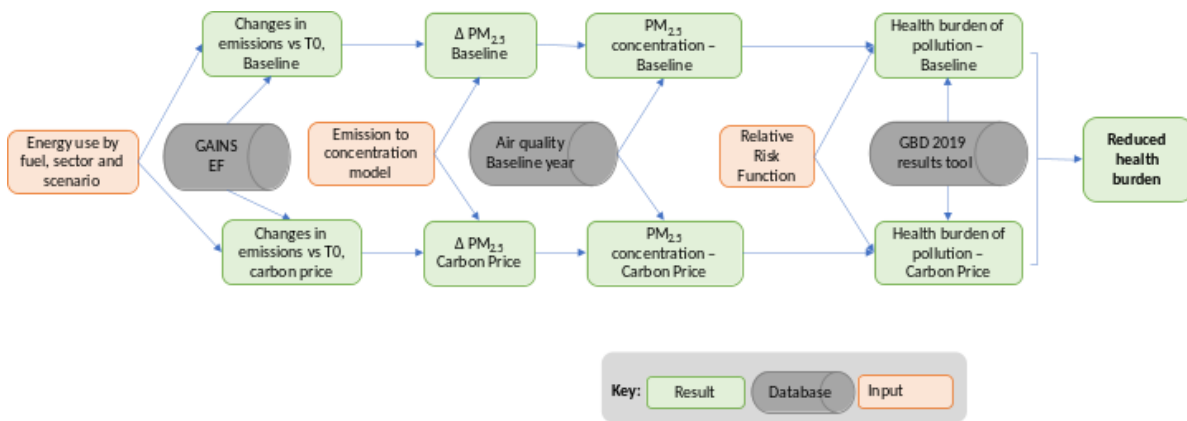


Figure 6.2: Methodology for estimating health impacts of a carbon price

findings (Section 6.8) and make the user aware of the limits (Section 6.9) of the air pollution module.

6.4 Methods for calculating emissions

In this section we explain how we calculate emissions in CPAT (Mitigation tab), using as input the fuel consumption by sector and over time, and emission factors (Figure 6.3). Emissions will be used to calculate concentrations of PM2.5 and O3.

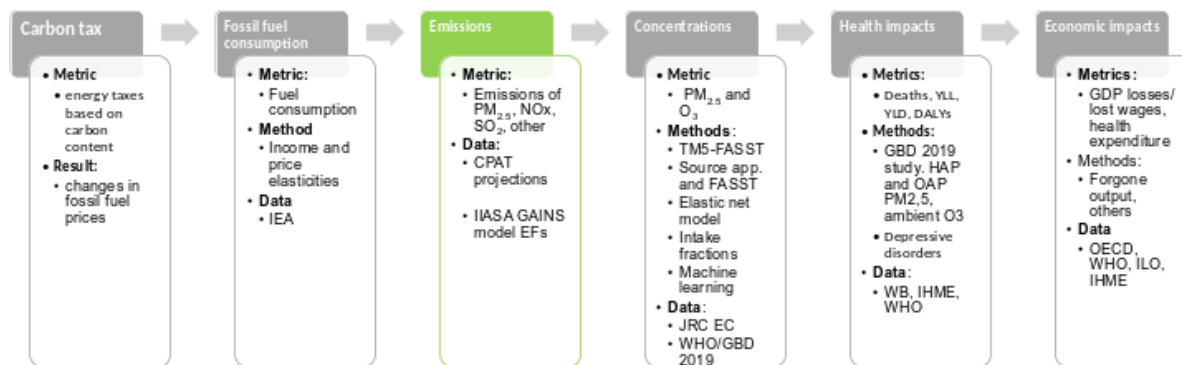


Figure 6.3: Overview of CPAT methodology, highlighting Emissions

6.4.1 Data sources for emissions

Input	Source
Energy consumption by fuel and sector in time	CPAT mitigation module. Based in IEA energy balances (IEA 2019) and others. See Mitigation tab documentation.
Emission Factors	GAINS model, IIASA (Wagner et al. (2020))
Radiative coefficients	GAINS model, IIASA (Wagner et al. (2020))

6.4.2 Emission factors from GAINS

Emissions for the baseline scenario are taken from the Greenhouse Gas - Air Pollution Interactions and Synergies (GAINS) Global Model, from the International Institute for Applied Systems Analysis (IIASA). The GAINS scenario selected as baseline is the ECLIPSE_V5a_CLE_base. This dataset was created in June 2015 and it covers emissions from 1990 to 2050 in five-year intervals. This baseline scenario considers current legislation (CLE) and committed legislation. The emission factors were grouped to reflect CPAT sectors and fuels, as described in Wagner et al. (2020).

The basic principle to estimate emissions in GAINS is presented in expression (Equation 6.1). Emissions are driven by activity levels (such as energy consumption), emissions factors that depend on the process and fuel type utilized (if any) and technology implementations that account for possible pollution control technologies (such as particulate filters, electrostatic precipitators, among many others). The emission factors used in CPAT include country specific technology implementations, according to the Current Legislation Scenario.

$$Emissions = FuelConsumption * Emission\ Factors \quad (6.1)$$

In CPAT, the pollutants included are PM2.5, NO_x, SO₂, CO₂, NMVOC, BC, OC, CH₄, CO, while the sectors and fuels for which we have emissions factors are presented in Table 6.2⁴.

Table 6.2: Emission factor sectors and fuels

Sector	Subsector	Biomass	Coal	Diesel	Gasoline	Jet	Kerosene	LPG	Gas	Other
						fuel				oil
Power		X	X	X	X				X	X
Residential		X	X	X	X		X	X	X	X
Transport	Road			X	X		X	X	X	
	trans- port Aviation					X				
Industries	Rail			X						
	Construction			X	X		X	X	X	
	Food and Forestry	X	X	X	X		X	X	X	X
	Mining & Chem- icals			X	X				X	
	Manufacturing	X	X	X	X		X	X	X	X
	Other	X	X	X	X		X	X	X	X
	Manu- factur- ing Services	X	X	X	X		X	X	X	X

⁴For “Other energy use”, we assume an EF equal to the maximum among the EFs of the rest of the subsectors.

Source: Own elaboration based on Wagner et al. (2020)

The EF from the current legislation scenario will change in time, as shown in Figure 6.4. In CPAT, the user can select the to use EFs that are variable in time or a constant value, from year 2015.

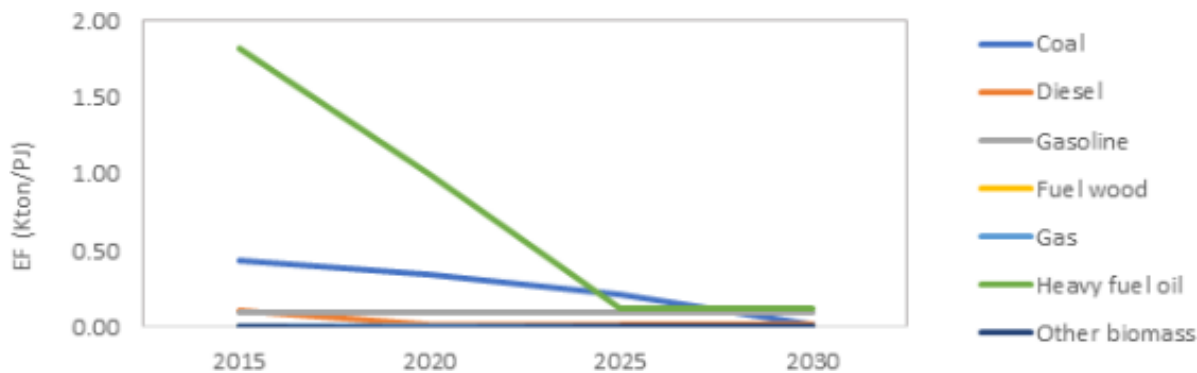


Figure 6.4: Example of emission factors for SO₂, for power plants in India

Source: Own elaboration based on Wagner et al. (2020)

The EF from GAINS are country specific for 89 countries. For countries not included in that group, we consider regional averages.

Figure 6.5 shows data quality categories for countries included in the GAINS model. In green is Category 1, for which there is high confidence in the data. In yellow is category 2, for which there is medium confidence and in red, is category 3, for which the level of confidence is low.

Source: Personal communication with Fabian Wagner. Category 1: High confidence, Category 2: Medium confidence Category 3: Low confidence.

6.4.3 Radiative forcing coefficients

Reducing local air pollutants will result in positive health impacts. However, the reduction of local pollutants can imply an increase in global warming, because of the cooling effect of some of these pollutants. Some local pollutants behave asymmetrically compared to GHGs: the more they are emitted, the more they cool the earth. Figure 6.6 presents a diagram of the cooling and warming effects of reducing pollutants.

Source: Shindell (2013)⁵. Solid lines indicate known impact; dashed lines indicate uncertain impact.

⁵Report available in https://www.ipcc.ch/site/assets/uploads/2018/02/WG1AR5_Chapter08_FINAL.pdf, visited on April 2020.

Country/region	CODE	QC	Country/region	CODE	QC
Afghanistan	AFG	3	Kyrgyzstan	KGZ	3
Albania	ALB	3	Laos	LAO	3
Argentina	ARG	2	Macedonia	MKD	3
Armenia	ARM	3	Malaysia	MYS	2
Azerbaijan	AZE	3	Mexico	MEX	2
Bangladesh	BGD	2	Middle_East	RMENA	3
Belarus	BLR	3	Mongolia	MNG	3
Bhutan	BTN	3	Myanmar	MMR	3
Bolivia	BOL	3	Nepal	NPL	2
Bosnia-Herz.	BIH	2	Nigeria	NGA	2
Brazil	BRA	2	North_Korea	PRK	3
Brunei	BRN	3	N-Africa (w/o Egypt)	RNAFR	3
Cambodia	KHM	3	Other_FSU	RFSU	3
Canada	CAN	2	Pakistan	PAK	3
Caribbean	RCARR	3	Paraguay	PRY	3
Centr. America	RCEAM	3	Peru	PER	2
Chile	CHL	2	Philippines	PHL	2
China	CHN	1	Oth S Africa	RSAFR	2
Colombia	COL	3	South Africa	ZAF	2
EastAfrica	REAFR	3	Moldova	MDA	3
Ecuador	ECU	3	Serbia	SRB	3
Egypt	EGY	2	South_Korea	KOR	1
Georgia	GEO	2	Sri_Lanka	LKA	3
Germany	DEU	1	Taiwan	TWN	3
India	IND	1	Tanzania	TZA	2
Indonesia	IDN	2	Thailand	THA	2
Iran	IRN	3	Turkey	TUR	2
Israel	ISR	2	Ukraine	UKR	2
Kazakhstan	KAZ	3	Uruguay	URY	3
Kenya	KEN	2	Venezuela	VEN	3
Saudi Arabia	SAU	3	W-Africa (w/o Nigeria)	RWAFR	3

Figure 6.5: Quality of input data. Data quality categories (QC)

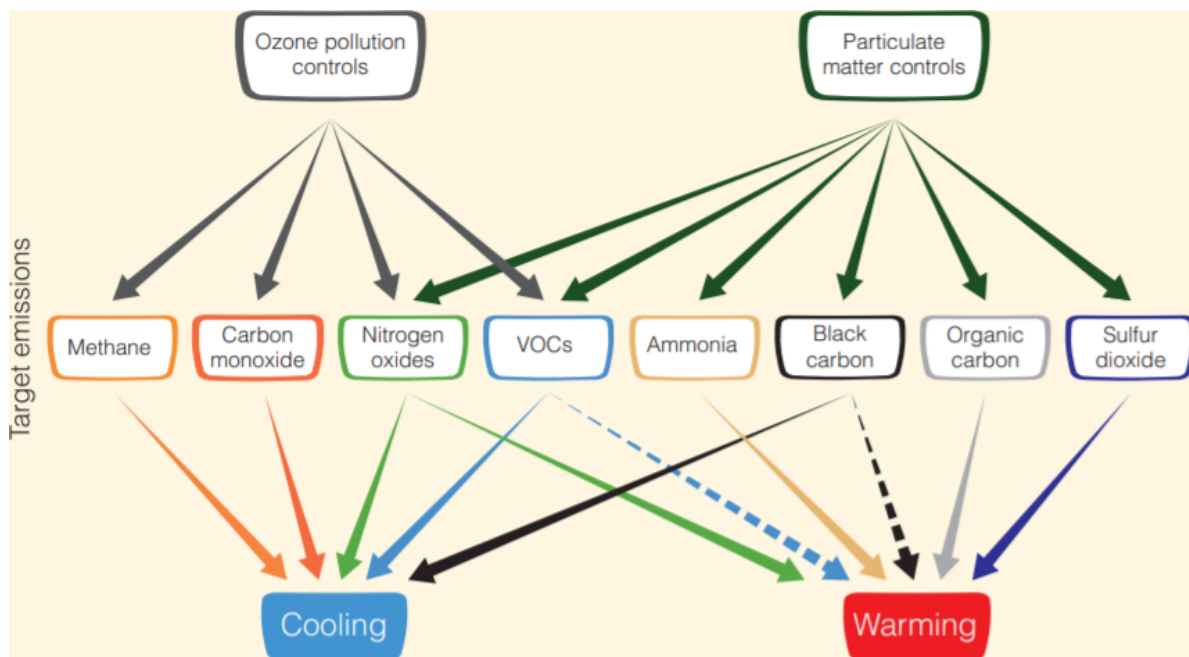


Figure 6.6: Diagram of the impact of pollution control on emissions and climate impact

CPAT will consider the net warming effects of reducing local pollutants, according to their Global Warming Potential in a hundred years (GWP100), using the regional values presented in Table 6.3.

Table 6.3: GWP100 coefficients used in CPAT

Region	CO	NH3	NO _x	PM_BC	PM_OC	SO ₂	VOC
Africa	1.989	-13.332	-7.058	356.463	-121.075	-85.172	6.154
Asia & Oceania	1.989	-13.332	-7.058	356.463	-121.075	-85.172	6.154
Eurasia	3.246	-18.162	-9.501	407.156	-138.559	-109.67	7.303
Europe	3.246	-18.162	-9.501	407.156	-138.559	-109.67	7.303
Middle East	1.989	-13.332	-7.058	356.463	-121.075	-85.172	6.154
North America	1.989	-13.332	-7.058	356.463	-121.075	-85.172	6.154

Source: GAINS model, IIASA.

Besides CO₂ emissions, CPAT will consider the Global Warming Potential of methane, using the GWP100 indicated in Table 6.4.

Table 6.4: GWP100 coefficients for CH4 used in CPAT

Substance	GWP100	Source
CH4	28.0	IPCC 5th assessment report

Source: IPCC and others (2014).

A list of substances with radioactive forcing impacts is presented in Table 6.5. The table indicates which substances are included in CPAT and in the UNFCCC framework.

Table 6.5: Substances with climate/radiative forcing impacts under UNFCCC and CPAT

Substance type	Substance	UNFCCC	CPAT
Greenhouse gases	CO2		
	CH4		
	N2O		
	HFCs		
	PFCs		
	SF6		
	NF3		
Short-lived climate forcers (SLCF)	BC		
	O3 (tropospheric)		*
	CH4		
	HFCs		
	SO2		
	NOx		
Precursors of SLCF	CO		
	NMVOG		
	SO2		
	NOx		
	NH3		
	OC		

Source: Own elaboration. (*) CPAT includes the health effects of ambient ozone, but not emissions of ozone.

6.5 Methods to relate emissions and ambient pollution

This chapter describes the options implemented in CPAT to link emissions and ambient pollution: i) TM5-FASST model, ii) Source apportionment information combined with FASST, iii)

Elastic Net model, iv) Intake fractions, and v) Machine learning (see Figure 6.7).

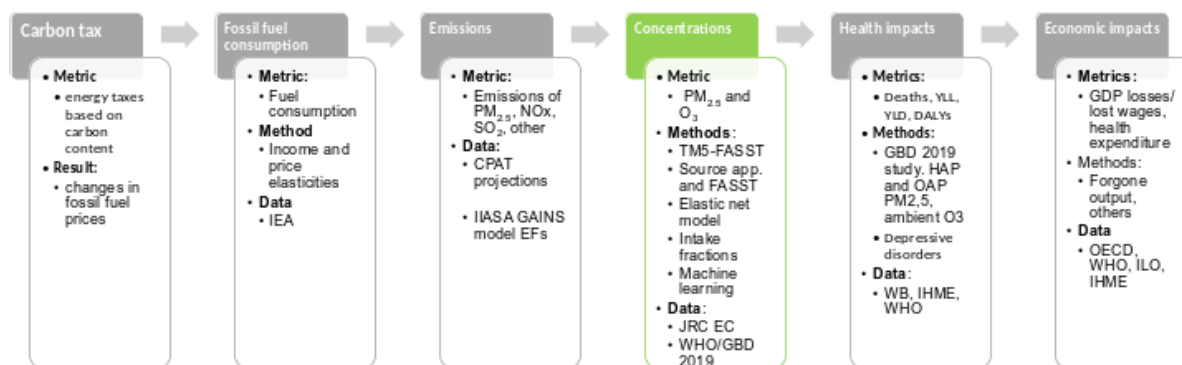


Figure 6.7: Concentration of PM_{2.5} and O₃, CPAT methodology overview

Table 6.6 describes the aggregation of sectors done in the air pollution tab, which in some cases differs from the sector used in the Mitigation tab.

Table 6.6: Source types in the Air pollution and Mitigation modules

Air pollution aggregation	Air pollution Subsector code	Manufacturing sub sectors	Mitigation sub sectors	Fuel used
Coal Power Plants	pow		Power	coa
Gas Power Plants				nga
Other Power Plants				oop bio
Road transport	rod		Road	multiple
Residential, services and construction	res		Residential	multiple
	cst		Construction	multiple
	srv		Services	multiple
Industries and other energy	mnf	irn	Iron and steel	multiple
		nfm	Non-ferrous metals	multiple
		mac	Machinery	multiple
		cem	Cement	multiple
	ft	Fuel transformation & transportation	multiple	
	mch	Mining & Chemicals	coa	
	omn	Other manufacturing	coa	
	oen	Other - energy use	multiple	
	ral	Rail	die	
	avi	Domestic Aviation*	jfu	

Air pollution aggrupation	Air pollution Subsector code	Manufacturing sub sectors	Mitigation sub sectors	Fuel used
Food & forestry	foo		Food & forestry (includes agriculture)	multiple

Source: Own elaboration. (*) considers emissions from departing and landing only.

6.5.1 Data sources to relate emissions and ambient concentrations

Table 6.7: Summary of data sources to relate emissions to ambient pollution

Input	Source
TM5-FASST model, from the European Commission Joint Research Center	Van Dingenen et al. (2018)
TM5-FASST mode, downscaled at a country level	Aleluia Reis (2020)
Elastic Net Model & Machine learning models	Renna and Reis (2021)
WHO source apportionment database	World Health Organization (2015)
Other source apportionment studies	World Bank (2020); World Bank (2019a) Lelieveld et al. (2015); Almeida et al. (2020); Gaita et al. (2014)
Intake fractions	Zhou et al. (2006); Apte et al. (2012)

6.5.2 Option 1: TM5-FASST

The Fast Scenario Screening Tool (FASST) is an emulator of the full TM5-CTM global chemical transport model. FASST is a source-receptor model with linearized relations between emissions and concentrations. This tool allows the modeling of ambient PM_{2.5} and O₃ concentrations.

FASST includes 56 source-receptor regions (see Figure 6.8) and the pollutants considered (as emissions) are SO₂, NO_x, NH₃, OC, NMVOC, Elemental Carbon, Primary Organic Matter⁶, PM_{2.5}⁷ and CH₄.

Source: Van Dingenen et al. (2018)

⁶POM is assumed to be equal to 1.3*OC

⁷Total PM_{2.5}= BC + POM + Other primary PM_{2.5}

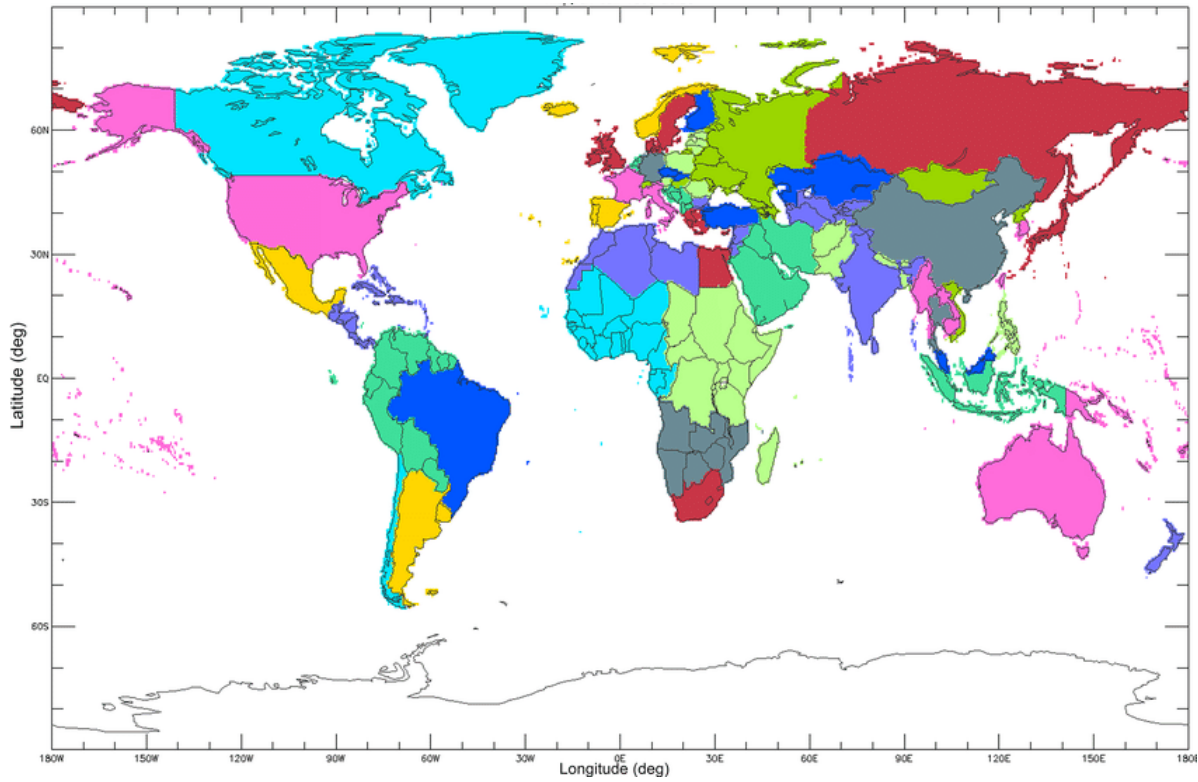


Figure 6.8: The 56 continental emission source regions in TM5-FASST

The coefficients from the source-receptor matrices are given by Equation 6.2 and the concentration in receptor y from component j are presented in Equation 6.3 - see Van Dingenen et al. (2018).

$$A_{ij} [x, y] = \frac{C_j(y)}{E_i(x)} \quad (6.2)$$

With $E_i(x) = 0.2E_{i,base}(x)$

Where:

A_{ij} : source-receptor matrix coefficient (annual mean responses) in $\mu\text{g}/\text{m}^3$

x : source region

y : receptor point

j : component (PM2.5 and O3)

i : precursor of j (BC, POM, SO2, NOx and OPM for $j = \text{PM2.5}$; and NOx, NMVOC, SO2 and CH4 for $j = \text{O3}$)

Ambient concentration in receptor y from component j is calculated using expression (Equation 6.3).

$$C_j(y) = C_{j,base}(y) + \sum_{k=1}^{n_x} \sum_{i=1}^{n_i} A_{ij} [x_k, y] * [E_i(x_k) - E_{i,base}(x_k)] * UrbanIncFactor \quad (6.3)$$

Where:

A_{ij} : source-receptor matrix coefficient (annual mean responses)

n_i : number of precursors i

n_x : number of source regions x

$E_i(x)$: emission rate (kg/yr) of precursor i at source x

$C_{j,base}(y)$: constant for pollutant j and location y

k : pollutant

The precursors for PM2.5 included are BC, POM, SO2, NOx and OPM (other particulate matter). Notice that NH3 emissions are not included in the analysis and are assumed to be constant over time.

The precursors of ozone considered are NOx, NMVOC, SO2 and CH4.

As mentioned, FASST contains results for 56 regions only. To produce source-receptor coefficients for every country inside those regions, we applied a down-scaling of FASST to produce country level coefficients. The methods are described in Aleluia Reis (2020).

In addition to the country down-scaling from Aleluia Reis (2020), we produced a downscale based in the population in the FASST regions and in the countries inside those regions, as presented in expression Equation 6.4. In some cases, we applied the population downscale, when the performance of the method described in Aleluia Reis (2020) is low.

$$A_{i,j,country} = A_{i,j,region} * \frac{\text{Population}_{region}}{\text{Population}_{country}} \quad (6.4)$$

If we multiply the emissions j from the modeled sectors by the corresponding $A_{i,j}$ coefficients, we obtain the ‘modeled’ contribution to i (where i is PM2.5 or O3) in CPAT, using expression Equation 6.5.

$$\text{Modeled } i_{t,s} = \sum_j \sum_s A_{i,j} * \text{Emissions}_{j,s,t} \quad (6.5)$$

6.5.2.1 From FASST spreadsheet to CPAT

In the spreadsheet version of FASST (provided by Rita Van Dingenen), there are two emission scenarios and each of them is compared to FASST baseline scenario (there are three scenarios in total). In CPAT, we do not use the FASST baseline scenario, but only two scenarios: baseline (as in CPAT) and carbon price (as in CPAT). We do not need to include the FASST baseline scenario in CPAT because to quantify the changes in PM2.5 (or in O3), attributed to the carbon tax, we subtract the results from the baseline and the carbon tax. In that operation, FASST baseline would be eliminated anyways and because of that is not needed.

Table 6.8 presents the operations in FASST spreadsheet and CPAT adaptations. In the last column of the table, I mention the ‘transformations’ to the SR coefficients used in CPAT, so the operations are simplified. These transformations yield the same changes in PM2.5 that we would obtain using the original steps performed in the spreadsheet of FASST, because all operations are linear.

Table 6.8: CPAT adaptations of TM5-FASST, spreadsheet version

FASST spreadsheet calculation		CPAT adaptations
Emissions	(<i>USER_CALC_1</i>)	
Uses BC emissions	$\text{delta}_{BC \rightarrow BC,1} = (Em_{BC,1} - Em_{FASST_{BC}}) * SR_{BC \rightarrow BC}$	In CPAT I multiply BC emissions by $SR_{BC \rightarrow BC} * urbanIncFactor = \mathbf{SR}_{BC, CPAT}$
Uses POM emissions= 1.3*OC	$\text{delta}_{POM \rightarrow POM} = (Em_{POM,1} - Em_{FASST_{POM}}) * SR_{POM \rightarrow POM}$	In CPAT I multiply POM emissions by $SR_{POM \rightarrow POM} * urbanIncFactor = \mathbf{SR}_{POM, CPAT}$
Uses Other PM emissions = PM2.5-BC-POM	$\text{delta}_{OPrPM2.5 \rightarrow OPrPM2.5,1} = (Em_{OPrPM2.5,1} - Em_{FASST_{OPrPM2.5}}) * SR_{BC \rightarrow BC}$	In CPAT I multiply Other PM2.5 emissions by $SR_{BC \rightarrow BC} * urbanIncFactor = \mathbf{SR}_{BC, CPAT}$
Uses SO2 emissions	$\text{delta}_{SO2 \rightarrow SO4,1} = (Em_{SO2,1} - Em_{FASST_{SO2}}) * SR_{SO2 \rightarrow SO4}$ $\text{delta}_{SO2 \rightarrow NO3,1} = (Em_{SO2,1} - Em_{FASST_{SO2}}) * SR_{SO2 \rightarrow NO3}$ $\text{delta}_{SO2 \rightarrow NH4,1} = (Em_{SO2,1} - Em_{FASST_{SO2}}) * SR_{SO2 \rightarrow NH4}$	In CPAT, I multiply the emissions of SO2 by $SR_{SO2 \rightarrow SO4} + SR_{SO2 \rightarrow NO3} + SR_{SO2 \rightarrow NH4} = \mathbf{SR}_{SO2, CPAT}$
Uses NOx emissions	$\text{delta}_{NOx \rightarrow SO4,1} = (Em_{NOx,1} - Em_{FASST_{NOx}}) * SR_{NOx \rightarrow SO4}$ $\text{delta}_{NOx \rightarrow NO3,1} = (Em_{NOx,1} - Em_{FASST_{NOx}}) * SR_{NOx \rightarrow NO3}$ $\text{delta}_{NOx \rightarrow NH4,1} = (Em_{NOx,1} - Em_{FASST_{NOx}}) * SR_{NOx \rightarrow NH4}$	In CPAT, I multiply the emissions of NOx by $SR_{NOx \rightarrow SO4} + SR_{NOx \rightarrow NO3} + SR_{NOx \rightarrow NH4} = \mathbf{SR}_{NOx, CPAT}$
Uses NH3 emissions	$\text{delta}_{NH3 \rightarrow SO4,1} = (Em_{NH3,1} - Em_{FASST_{NH3}}) * SR_{NH3 \rightarrow SO4}$ $\text{delta}_{NH3 \rightarrow NO3,1} = (Em_{NH3,1} - Em_{FASST_{NH3}}) * SR_{NH3 \rightarrow NO3}$	In CPAT, we do not have NH3 emissions

FASST spreadsheet calculation	
Emissions (<i>USER_CALC_1</i>)	CPAT adaptations
$\text{delta}_{NH3 \rightarrow NH4,1} = (Em_{NH3,1} - Em_{FASST_{NH3}}) * SR_{NH3 \rightarrow NH4}$	

Where EmFASST are FASST base emissions and $Em_{p,1}$ are emissions from pollutant p in scenario 1.

In the tab *USER_CALC_1*, delta_{BC} and delta_{POM} are then multiplied by the urban incremental factor.

$$d_{BC,1} = \text{delta}_{BC,1} * \text{urbIncfactor} \quad (6.6)$$

$$d_{POM,2} = \text{delta}_{POM,1} * \text{urbIncfactor} \quad (6.7)$$

And the following aggregations among deltas are made:

$$d_{SO4,1} = \text{delta}_{SO2 \rightarrow SO4,1} + \text{delta}_{NOx \rightarrow SO4,1} + \text{delta}_{NH3 \rightarrow SO4,1} \quad (6.8)$$

$$d_{NO3,1} = \text{delta}_{SO2 \rightarrow NO3,1} + \text{delta}_{NOx \rightarrow NO3,1} + \text{delta}_{NH3 \rightarrow NO3,1} \quad (6.9)$$

$$d_{NH4,1} = \text{delta}_{SO2 \rightarrow NH4,1} + \text{delta}_{NOx \rightarrow NH4,1} + \text{delta}_{NH3 \rightarrow NH4,1} \quad (6.10)$$

$$d_{OPrPM2.5,1} = \text{delta}_{OPrPM2.5 \rightarrow OPrPM2.5,1} \quad (6.11)$$

Finally, the total change in PM2.5 concentrations in scenario 1 is:

$$\text{TOTdPM}_1 = d_{BC,1} + d_{POM,1} + d_{SO4,1} + d_{NO3,1} + d_{NH4,1} + d_{OPrPM2.5,1} \quad (6.12)$$

Where TOTdPM_1 is the change in concentration with respect to FASST Baseline.

The same procedure is applied to calculate TOTdPM_2 , using the emissions of the scenario 2. TOTdPM_2 is the change in PM2.5 from scenario 2 versus FASST baseline scenario.

Then, in tab **RESULTS**, the change in PM2.5 among scenario 2 and scenario 1 is equal to $\text{TOTdPM}_2 - \text{TOTdPM}_1$. Because all equations are linear, we do not need to use FASST baseline emissions when we want to calculate changes in PM2.5 from two scenarios in CPAT.

6.5.3 Option 2: Source apportionment information

An alternative to the previous approach is to use source apportionment information, either from the WHO Source Apportionment (World Health Organization (2015)) database or from another source. The user might have access to local studies regarding the contribution to ambient PM_{2.5} from different emission sources and that information could be manually entered into CPAT.

The WHO database contains source apportionment information for 317 locations in 46 countries. Figure 6.9 presents the average contributions by sector in the regions of the world covered by the database.

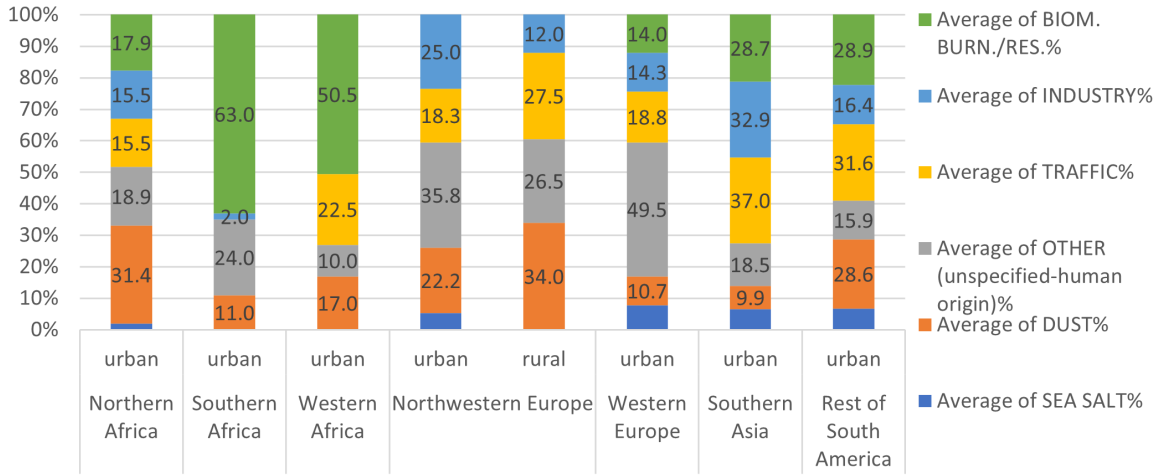


Figure 6.9: Average source apportionment for PM_{2.5}, selected regions of the world

Source: WHO database on local source apportionment studies

CPAT can combine the information from source apportionment studies with the source apportionment result from applying the TM5-FASST coefficients. For each sector, we estimate an adjustment factor, AF_s , to TM5-FASST coefficients, such that the external source contribution by sector will be met in the baseline year to. The adjustment factor for each sector s is calculated as:

$$AF_s = \frac{\text{ShareFASST}_{s,to}}{\text{ShareExternal}_s} \quad (6.13)$$

Where:

AF_s : Adjustment factor for sector s (s = coal power plants, gas power plants, other power plants, ground level road, residential-construction-services, agriculture, other sectors).

ShareFASST_s: % Contribution to ambient PM2.5 from sector *s*, calculated using FASST coefficients

ShareExternal_s: % Contribution to ambient PM2.5 from sector *s*, according to user’s input or to WHO database.

The modeled ambient PM2.5 under this option in CPAT is calculated as follows.

$$\text{Modeled PM2.5}_t = \sum_p \sum_s AF_s * \text{FASST}_{p,s} * \text{Emissions}_{p,s,t} \quad (6.14)$$

In CPAT, we have uploaded the source apportionment information for the 46 countries included in the WHO database, as well as additional studies covering additional countries (see Table 6.10 for the country coverage of each study). The correspondence between the sectors in the WHO database and CPAT air pollution sectors is presented in Table 6.9.

Table 6.9: Matching from WHO database sectors and CPAT air pollution tab sectors

WHO database sectors	CPAT AP sectors
Industry	Coal Power Plants
Industry	Gas Power Plants
Industry	Other Power Plants
Traffic	Road transport
Industry / Domestic fuel burning	Residential, services and construction
Industry	Industries and other energy
Unspecified source of human origin	Food & forestry (includes agriculture)
Natural sources (dust and sea salt)	Unknown (not modeled, natural, outside borders)

Source: Own elaboration. The WHO sector “Unspecified source of human origin” includes secondary formation of PM2.5 and it’s distributed among all CPAT sectors, including the “unknown” category in the proportions of each sector calculated using FASST coefficients.

CPAT allows the user to input other source apportionment distribution (manual input) and also includes a default distribution for most countries, based in the WHO database. The default source apportionment distribution is equal to the regional average, that can be used if the country is not covered in the WHO database. The information source used is indicated in the Air pollution module, under the section “Calibration options from the Dashboard/MSTInputs tab”.

Table 6.10 presents the country coverage of each of the studies preloaded in CPAT.

Table 6.10: Countries covered by source apportionment studies in CPAT

Study Countries covered

World Argentina, Australia, Bangladesh, Belgium, Brazil, Canada, Chile, China, Costa Rica,
 Health Denmark, Egypt, Estonia, Finland, France, Germany, Ghana, Greece, India,
 Or- Indonesia, Ireland, Italy, Japan, Korea, Kuwait, Macedonia, FYR, Malaysia, Mexico,
 ga- Mongolia, Netherlands, New Zealand, Norway, Pakistan, Philippines, Poland,
 ni- Portugal, Saudi Arabia, South Africa, Spain, Sri Lanka, Sweden, Switzerland,
 za- Thailand, Turkey, United Kingdom, United States, Vietnam

tion

(2015)

World Bosnia and Herzegovina

Bank

(2020)

Almeida Greece, Kazakhstan, Hungary, Moldova, Croatia, Serbia, Albania, Bosnia and
 et al. Herzegovina, Poland, Macedonia, FYR, Tajikistan

(2020)

Lelieveld China, Tukey

et al.

(2015)

World Macedonia

Bank

(2019a)

Gaita Kenya (assumed same results for Rwanda)

et al.

(2014)

6.5.4 Option 3: Elastic Net model and OLS model

CPAT also offers the option to apply the results of an elastic net regularization method to link emissions by sector to ambient concentrations of PM_{2.5} and O₃ (Renna and Reis (2021)). The ambient concentrations predicted represent population weighted averages per country. At the moment CPAT offers the elastic net model option only for PM_{2.5}.

The results of the elastic net model are combined with an OLS model. The results of the OLS model are used only to distribute the contribution of modeled PM_{2.5} among CPAT sectors, while the elastic net model is used to predict total ambient concentrations of PM_{2.5}.

The following table summarizes the data sources used to develop the elastic net and OLS models.

Variable

Data source

Emissions

CAMS Global Anthropogenic v4.2, 2000-2020, monthly, 0.1°

Concentrations

CAMS Global Reanalysis (EAC4) monthly averaged fields (Inness et al. (2019)), for 2003-2019, PM2.5 and Ozone

Population

2020 UN WPP-Adjusted Population Count, v4.11, from the NASA Socioeconomic Data and Applications Center (SEDAC) (CIESIN 2020).

Climate variables

Monthly data, 0.1 degrees resolution from TerraClimate. Variables used: precipitation, maximum temperature, minimum temperature, wind speed, vapor pressure deficit in kPa.

Wind direction from ERA-5 Reanalysis Monthly Means

Source: Based on Renna and Reis (2021)

The model considers the emissions of BC, OC, NH₃, SO₂ and NMVOC. The sectoral aggregation of the models is the following:

- AGR (Agriculture)
 - Agricultural waste burning
 - Agriculture livestock
 - Agriculture soils
- ROA (Road transportation)
 - Road transportation
- INX (industry)
 - Industrial process
- POW (Energy Power generation)
 - Power generation
 - Fugitives
- SER (Buildings including residential, commercial and services)

- Residential and other sectors
- OTR (Off-road transportation)
 - Off Road transportation
- OTH (Others, including the emissions not considered in the sectors above)
 - Solid waste and wastewater
 - Solvents

The data sources and methods are described in more detail in Renna and Reis (2021). In the next subsections we describe the implementation of the elastic net and OLS models in CPAT.

6.5.4.1 Elastic net model

As mentioned above, the elastic net model is used to predict total ambient PM2.5 in CPAT. The functional form and the adaptations made to the original coefficients of the model is detailed in the following paragraphs.

Monthly concentrations of PM2.5

The linear regressions developed to predict monthly levels of PM2.5 takes the form indicated in expression Equation 6.15 for each country.

$$PM2.5_m = \alpha + \sum_{s,p} \beta_{s,p} * E_{s,p,m} + \gamma_1 * PPT_m + \gamma_2 * TMIN_m + \gamma_3 * TMAX_m + \gamma_4 * VPD_m + \gamma_5 * WS_m + \gamma_6 * O3_m \quad (6.15)$$

Where:

m = Months of the year, from 1 to 12

$s \in \{agr, roa, pow, inx, otr, oth, ser\}$

$p \in \{BC, OC, NH_3, NO_x, NMVOC, SO_2\}$

$PM2.5_m$ = Concentration of PM2.5 in month m , in $\mu g/m^3$

$O3_m$ = Concentration of O_3 in month m , in $6mDMA8h^8$

$E_{s,p,m}$ = Emissions of sector s and pollutant p in month m , in Tg

⁸6mDMA8h corresponds to the seasonal (six-month period with the highest mean) 8-h daily maximum concentration metric

PPT_m = Accumulated precipitation in mm, month m

$TMIN_m$ = Minimum temperature in deg C month m

VPD_m = Mean vapor pressure deficit in kPa, month m

WS_m = wind speed in $\frac{m}{s}$, month m

WD_m = Wind direction in degrees, month m

$T_{p,m}$ = composite index from the sum of total emissions of pollutant p , in month m

$T_{s,m}$ = composite index from the sum of total emissions of sector s , in month m

ϕ_m = Monthly fixed effects

ε = Error term

Annual concentrations of PM2.5

In CPAT, we work on an annual basis, while the elastic net model was developed to predict PM2.5 in a monthly basis. Thus, we adapt the elastic net model results to predict annual concentration of PM2.5, as explain below.

Each month of the year will have a weight according to its number of days, equal to φ_m . For instance, for February, it's weight in the annual average is $\varphi_2 = 28/365$.

The weighted average PM2.5 will be calculated according to expression .

$$PM2.5 = \sum_m \varphi_m * PM2.5_m \quad (6.16)$$

Which can be written as expression Equation 6.17.

$$PM2.5 = \alpha + \sum_{s,p} \beta_{s,p} * \overline{E_{s,p}} + \gamma_1 * \overline{PPT} + \gamma_2 * \overline{TMIN} + \gamma_3 * \overline{TMAX} + \gamma_4 * \overline{VPD} + \gamma_5 * \overline{WS} + \gamma_6 * \overline{WD} + \sum_s \delta_s \quad (6.17)$$

Where:

$\overline{E_{s,p}}$ = average (simple) monthly emissions of sector s and pollutant p

\overline{PPT} = average (weighted) monthly precipitations

\overline{TMIN} = average (weighted) $TMIN$

\overline{TMAX} = average (weighted) $TMAX$

\overline{VPD} = average (weighted) vapor pressure deficit

\overline{WS} = average (weighted) wins speed

\overline{WD} = average (weighted) wind direction

$\overline{\phi}$ = average (weighted) monthly fixed effect

T_p = composite index from the sum of total emissions of pollutant p in all the months of the year

$w_{p,m}$ = share of emissions of pollutant p in month m , $T_{p,m}$, such that $\sum_{m=1}^{12} w_{p,m} = 1$.

T_s = composite index from the sum of total emissions of sector s in all the months of the year

$w_{s,m}$ = share of emissions of sector s in month m , $T_{s,m}$, such that $\sum_{m=1}^{12} w_{s,m} = 1$.

Annual concentration of PM2.5 in CPAT

In CPAT, we group and consider constant all the weather variables, together with the intercept of the model and monthly fixed effects.

For each country, we define a weather constant equal to:

$$Weather = \gamma_1 * \overline{PPT} + \gamma_2 * \overline{TMIN} + \gamma_3 * \overline{TMAX} + \gamma_4 * \overline{VPD} + \gamma_5 * \overline{WS} + \gamma_6 * \overline{WD} \quad (6.18)$$

Where $\overline{VAR} = \sum_m \varphi_m * VAR_m$

We define new constants, according to expressions Equation 6.19 to Equation 6.26.

$$\delta'_s = \delta_s * \sum_m \varphi_m * w_{s,m} \quad (6.19)$$

$$\lambda'_p = \lambda_p * \sum_m \varphi_m * w_{p,m} \quad (6.20)$$

$$\mu' = \mu * \sum_m \varphi_m * w_{NOx,m} * w_{NH3,m} \quad (6.21)$$

$$\nu' = \nu * \sum_m \varphi_m * w_{SO2,m} * w_{NH3,m} \quad (6.22)$$

$$\xi' = \xi * \sum_m \varphi_m * w_{SO2,m} * w_{NOx,m} \quad (6.23)$$

$$\theta'_s = \theta_s * \sum_m \varphi_m * w_{s,m} * WS_m * WD_m \quad (6.24)$$

$$\beta'_{s,p} = \beta_{s,p} / 12 \quad (6.25)$$

$$\beta''_{s,p} = (\beta'_{s,p} + \lambda'_p) \quad (6.26)$$

And we estimate annual PM2.5 using expression Equation 6.27.

$$PM2.5 = \alpha + Weather + \bar{\phi} + \sum_{s,p} \beta_{s,p} * \overline{E_{s,p}} + \sum_s \delta'_s * T_s + \sum_p \lambda'_p * T_p + \mu' * T_{NOx} * T_{NH3} + \nu' * T_{SO2} * T_{NH3} \quad (6.27)$$

The contribution of each sector to PM2.5 will be calculated according to expression Equation 6.28.

$$PM2.5_s = \sum_p \beta'_{s,p} * T_{p,s} + \delta'_s * T_s + \sum_p \lambda'_p * T_{p,s} + \mu' * T_{NOx,s} * T_{NH3,s} + \nu' * T_{SO2,s} * T_{NH3,s} + \xi' * T_{SO2,s} * T_{NOx,s} \quad (6.28)$$

Grouping terms, we can write the contribution to PM2.5 by sector as indicated in expression Equation 6.29.

$$PM2.5_s = \sum_p (\beta'_{s,p} + \lambda'_p) * T_{p,s} + (\delta'_s + \theta'_s) * T_s + \mu' * T_{NOx,s} * T_{NH3,s} + \nu' * T_{SO2,s} * T_{NH3,s} + \xi' * T_{SO2,s} * T_{NOx,s} \quad (6.29)$$

Let's call $\beta''_{s,p} = (\beta'_{s,p} + \lambda'_p)$ and $\delta''_s = (\delta'_s + \theta'_s)$ and write $PM2.5_s$ as in expression Equation 6.30.

$$PM2.5_s = \sum_p \beta''_{s,p} * T_{p,s} + \delta''_s * T_s + \mu' * T_{NOx,s} * T_{NH3,s} + \nu' * T_{SO2,s} * T_{NH3,s} + \xi' * T_{SO2,s} * T_{NOx,s} \quad (6.30)$$

Where:

$T_{p,s}$ = composite index from the sum of total emissions of pollutant p in sector s , including all the months of the year

The term $\alpha + Weather + \bar{\phi} + \varepsilon_m$ is not sector specific and it is considered a constant in CPAT.

The term Equation 6.31 is also non-sector specific and is relating the interactions across emissions of the different sectors.

$$\mu' * (T_{NOx} * T_{NH3} - \sum_s T_{NOx,s} * T_{NH3,s}) + \nu' * (T_{SO2} * T_{NH3} - \sum_s T_{SO2,s} * T_{NH3,s}) + \xi' * (T_{SO2} * T_{NOx} - \sum_s T_{SO2,s} * T_{NOx,s}) \quad (6.31)$$

6.5.4.2 OLS model

As mentioned before, in CPAT we apply the results of an OLS model to quantify the percent contribution of each sector to ambient PM2.5, while we use the elastic net model to predict total concentrations.

The OLS model has the functional form in expression Equation 6.32.

$$PM2.5_m = \alpha + \sum_s \delta_s * \widehat{T}_{s,m} + \gamma_1 * PPT_m + \gamma_2 * TMIN_m + \gamma_3 * TMAX_m + \gamma_4 * VPD_m + \gamma_5 * WS_m + \gamma_6 * W \quad (6.32)$$

Where $\widehat{T}_{s,m}$ is a composite index of total normalized emissions in month m and sector s . The procedure to normalize emissions is explained below.

Normalization of emissions for OLS model

For each country, let's call normalized emissions by sector and pollutant and month, $\widehat{E}_{s,p,m}$, that is calculated using expression Equation 6.33.

$$\widehat{E}_{s,p,m} = \frac{E_{s,p,m} - \text{Min}_{s,p}}{\text{Max}_{s,p} - \text{Min}_{s,p}} \quad (6.33)$$

Where:

$E_{s,p,m}$: emissions in month m per pollutant p and sector s

$\text{Min}_{s,p}$: Min emission across months for pollutant p and sector s

$\text{Max}_{s,p}$: Max emission across months for pollutant p and sector s

Then, the index $\widehat{T}_{s,m}$ is calculated using expression Equation 6.34.

$$\widehat{T}_{s,m} = \sum_p \widehat{E}_{s,p,m} \quad (6.34)$$

In CPAT, we do not calculate monthly emissions, but annual emissions, thus, the normalization of emissions and the index of total normalized emissions by sector considers annual emissions by sector and pollutant.

6.5.5 Option 4: Intake fractions

Another option in CPAT to relate emissions to ambient concentration of PM2.5 is using intake fractions. Intake fractions were defined in Bennett et al. (2002) as the integrated incremental intake of a pollutant, summed over all exposed individuals, and occurring over a given exposure time, released from a specified source or source class, per unit of pollutant emitted. Intake fractions measure the change in population-weighted ambient concentrations of a pollutant (PM2.5 in this case) per unit of pollutant emitted Cropper et al. (2012). Zhou et al. (2006) defined intake fractions as the fraction of material or its precursors released from a source that is eventually inhaled or ingested by a population. Intake fractions are defined by Equation 6.35.

$$iF = \frac{\sum_{i=1}^N P_i * C_i * BR}{Q} \quad (6.35)$$

Where:

iF: Intake Fraction, inhaled grams of PM2.5 per ton (ppm) of emissions

P_i : population residing in a region located at a distance i from the emission source

ΔC_i : change in ambient concentration of PM2.5 g/m³

BR: Average breathing rate in cubic meters per day m³/day

Q : Emissions rate tonne/day

From Equation 6.35, rearranging the terms, we can express changes in concentration weighted average as shown in Equation 6.36.

$$\sum_{i=1}^N P_i * C_i = \frac{iF * Q}{BR} \quad (6.36)$$

Intake fractions are influenced by the emissions height, as illustrated in Figure 6.10. Ground level emissions are usually inhaled in a major proportion, compared with emissions from a high stack.

Source: Parvez, Lamancusa, and Wagstrom (2017)

At the same time, intake fractions depend on the population density at different distances from the emission source. As illustrated in Figure 6.11, higher population concentrations will increase the intake fraction value, since more people is inhaling pollution.

Source: Lamancusa, Parvez, and Wagstrom (2017)

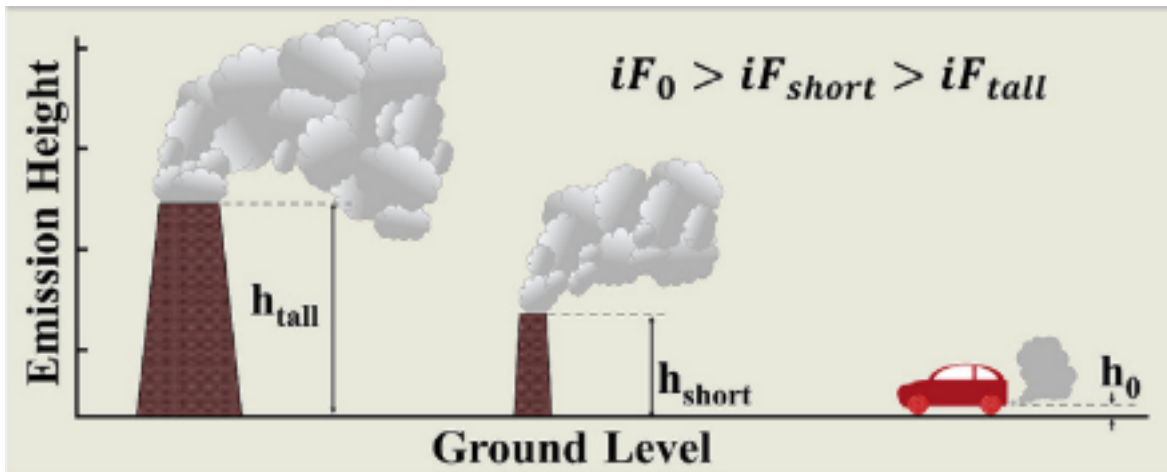


Figure 6.10: Illustration of Intake fraction variation according to emissions height

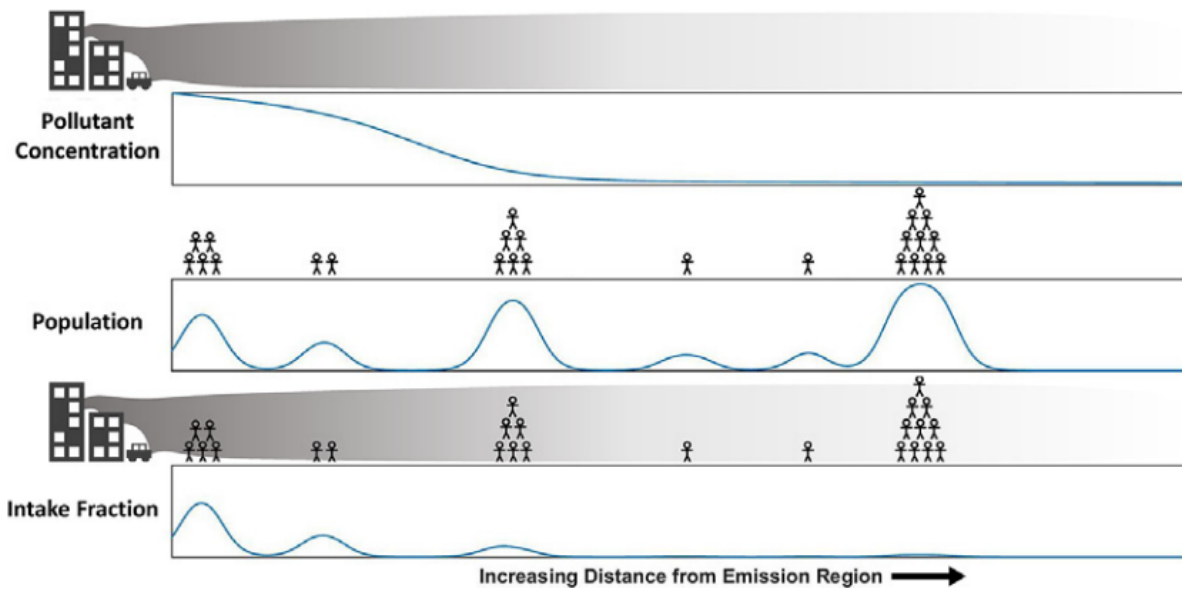


Figure 6.11: Illustration of intake fractions variation according to distance from the source and population concentration.

6.5.5.1 Intake fractions for ground level, low and high stack emission sources

In CPAT, for sources different than power plants, we use the results from Apte et al. (2012). The study estimates intake fractions for more than 3,600 cities, for ground level sources and for direct emissions of PM2.5.

In the case of secondary pollutants, we will scale up the ground-level secondary intake fractions from Humbert et al. (2011), presented in Table 6.11, using the ratio between primary PM2.5 intake fractions from Apte et al. (2012) and Humbert et al. (2011), as indicated in Equation 6.37.

$$iF_{\text{secondary pollutant}} = \frac{iF_{PM2.5, Apte}}{iF_{PM2.5, Humbert}} * iF_{\text{secondary Humbert}} \quad (6.37)$$

Table 6.11: Intake fractions (ppm) for ground level PM2.5

Pollutants		Urban	Rural	Remote
Primary PM2.5	Ground-level PM2.5	44	3.8	0.1
	high-stack	11	1.6	0.1
	low-stack	15	2.0	0.1
Secondary PM2.5	SO2	0.99	0.79	0.05
	NOx	0.2	0.17	0.01
	NH3	1.7	1.7	0.1

Source: Humbert et al. (2011)

For non-ground level sources, in which emissions take place through high or low stacks, the iF is estimated according to Equation 6.38.

$$iF_{\text{high/low}} = iF_{PM2.5, Fantke} * \frac{iF_{PM2.5, Humbert, \text{high/low}}}{iF_{PM2.5, Humbert, \text{groundlevel}}} \quad (6.38)$$

6.5.5.2 Intake fractions from power plants

Power plants emissions are released from tall smokestacks and consequently are likely to be transported long distances. In order to include the geographically extended effect of power plants emissions into the analysis, we will use intake fractions that were developed specifically for this sector, following Zhou et al. (2006).

Zhou et al. (2006) estimates intake fractions for 29 power plants in China and proposes a methodology to calculate intake fractions in other regions of the world using population and

precipitation data. The authors extrapolated the intake fraction results to other sites using regression analysis (see Table 6.12). This methodology (Zhou et al. (2006)) was applied by on the spreadsheet model developed by Parry et al. (2014) and subsequent IMF iterations.

CPAT intake fractions use updated data regarding power plant’s location and population distribution around them, together with differentiating exposed population inside country borders and outside countries. The methodology is illustrated in Figure 6.12.

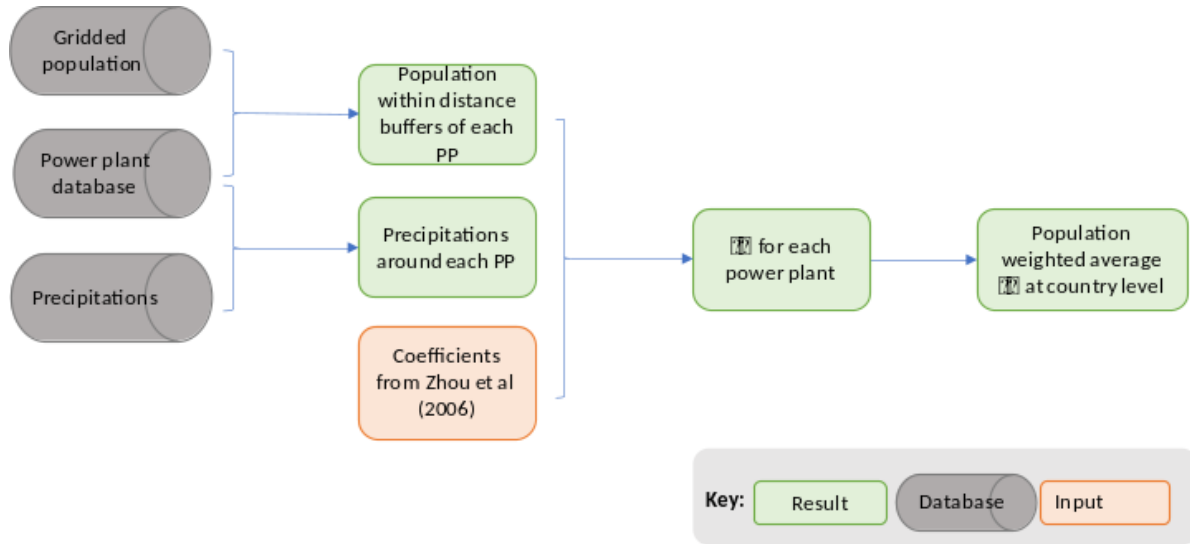


Figure 6.12: Methodology for estimating intake fractions for power plants

Source: Own elaboration

The following table provides a comparison between the approach implemented by Parry et al. (2014) and CPAT.

Parry 2014

CPAT

Methodology

Coefficients from Zhou et al. (2006) (Table 4)

Coefficients from Zhou et al. (2006) (Table 6)

Power plants data

CARMA

2009 data.

110 countries

2,400 coal plants

2,000 natural gas plants

Global Power Plant Database⁹ (Global Energy Observatory, Google, KTH Royal Institute of Technology in Stockholm, Enipedia, World Resources Institute (2018)).

Updated in 2019

164 countries

2,390 coal plants

3,922 gas power plants

2,290 oil power plants

Gridded population

LandScan- 2010 Population

Earth Data¹⁰, 2020 pop (Center for International Earth Science Information Network (CIESIN) Columbia University 2018b)

Exposed population

Population within 2000 km (above 25). No distinction between inside and outside the country

Population within 2000 km (distributed in age ranges). Distinction between inside and outside (relevant for country analysis).

Precipitations

-

Precipitations

Breathing rate

20 m³/day (from Zhou et al. (2006))

20 m³/day

Weight for averages at country level

Coal used (based on CO₂ emissions)

Power generation (average years available or estimated generation). If no value for generation, then we assigned a simple average.

⁹Data available at <http://datasets.wri.org/dataset/globalpowerplantdatabase>

¹⁰Data available in <https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-rev11/data-download>

As indicated in the previous table, CPAT will use the Global Power Plant Database (Global Energy Observatory, Google, KTH Royal Institute of Technology in Stockholm, Enipedia, World Resources Institute (2018)), which includes approximately 28,700 geolocated power plants in 164 countries, accounting for 80% of global installed capacity (Byers et al. (2018)). The database contains 2,390 coal plants, 3,922 gas power plants and 2,290 oil power plants.

The team decided to use this database, since CARMA database has not been updated since 2012 (Byers et al. (2018)). Figure 6.13 shows, as an example, the location of the coal power plants included in the database.

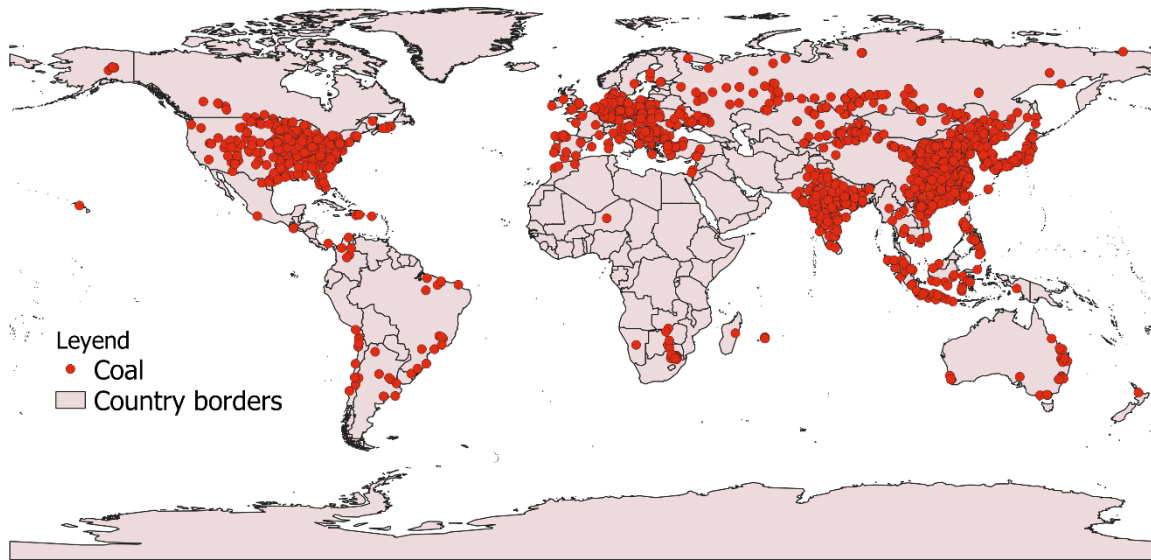


Figure 6.13: Location of Coal Power Plants

Source: Based on Global Energy Observatory, Google, KTH Royal Institute of Technology in Stockholm, Enipedia, World Resources Institute (2018) ¹¹

Zhou et al. (2006) requires estimating population around different distances of each power plant. To estimate population inside different distance buffers, gridded population data was obtained from the Center for International Earth Science Information Network (CIESIN), from Columbia university. The population-count raster file used consists of estimates of human population (number of persons per pixel), consistent with national censuses and population registers, for the years 2000, 2005, 2010, 2015, and 2020 (CPAT analysis is based on 2020). The data set consists of global raster files at 30 arc-second horizontal resolution (approximately 1 km at the equator). The 30 arc-second¹² data were aggregated to 2.5 arc-minute, 15 arc-minute, 30 arc-minute and 1 degree resolutions (Center for International Earth Science Information Network - CIESIN - Columbia University (2018)). The team decided to use this dataset,

¹¹Country borders from Columbia National Administrative Boundaries, v3 (2000), available in <https://sedac.ciesin.columbia.edu/data/set/gpw-v3-national-admin-boundaries/data-download>

¹²A 30 arc-second resolution is equivalent to 1x1 km in the equator.

instead of Landsat 2017, since the former is available free of charge, and both sources provide equivalent quality and resolution.

The methodology in Zhou et al. (2006) allows the inclusion of the variable precipitations. Precipitations data¹³ was obtained from The Millennium Ecosystem Assessment (MA) Climate and Land Cover, v1 (1901 – 2000)¹⁴ (Reid and Raudsepp-Hearne (2005)). This dataset contains raster grids for monthly average precipitations.

For each power plant, we built a distance buffer of 40 kilometers and we compute the average precipitation inside that buffer. That variable is then used to predict intake fractions for each power plant, according to in Zhou et al. (2006).

The regression coefficients from Zhou et al. (2006), presented in Table 6.12, will be used to estimate an intake fraction for each power plant in each country.

Table 6.12: Coefficients for intake fractions from Zhou et al. (2006), Table 6

Pollutant j	1 - Popu- lation within 100 km		2 - Population between 100 and 500 km	3 - Population between 500 and 1000 km	4 - Popu- lation beyond 1000 km	5 - Precipi- tation		
	R2							
SO2	0.96	9.90E-08	**	1.30E-08	**	3.00E-09	1.80E-09	6.30E-10
PM1	0.96	1.50E-07	*	2.30E-08	**	1.10E-08	** 3.90E-09	1.70E-09
PM3	0.92	1.40E-07	*	1.70E-08	**	6.40E-09	3.00E-09	** 2.40E-09
PM7	0.91	9.90E-08	**	8.90E-09	*	3.10E-09	1.50E-09	* 1.20E-09
PM13	0.89	6.70E-08	**	4.30E-09		9.40E-10	7.30E-10	4.60E-10
SO4	0.95	2.40E-08		7.90E-09	*	6.90E-09	** 2.60E-09	** 1.20E-09

¹³<https://www.esrl.noaa.gov/psd/data/gridded/tables/precipitation.html>

¹⁴Data available in <https://sedac.ciesin.columbia.edu/data/set/ma-climate-land-cover/metadata>

Pollutant j	R2	1 - Popu- lation within 100 km	2 - Population between 100 and 500 km	3 - Population between 500 and 1000 km	4 - Popu- lation beyond 1000 km	5 - Precipi- tation		
		NO3	0.93	4.30E-08		1.30E-08	**	3.50E-09

Source: Zhou et al. (2006).

Notes: Estimate significant at 0.05 level. Estimate significant at 0.10 level. Population variables in millions; precipitation in mm/yr

The intake fraction for each power plant is calculated according to Equation 6.39, using the coefficients from Table 6.12.

$$iF_{p, j, l} = \sum_{i=1}^4 \beta_{i,j} * Pop_{i, l} + \beta_{5, j} * Precipitation_p \quad (6.39)$$

Where:

$iF_{p, j, c}$: Intake fraction for power plant p , pollutant j , location l

$Pop_{i, l}$: Population at distance i , location l

$Precipitation_p$: Precipitations around plant p

$\beta_{i,j}$: Regression coefficients for pollutant j , location l

$$i = \begin{cases} 1, & \text{Population within 100 km} \\ 2, & \text{Population between 100 and 500 km} \\ 3, & \text{Population between 500 and 1000 km} \\ 4, & \text{Population within 1000 and 2000 km} \end{cases}$$

j = SO2, PM1, PM3, PM7, PM13, SO4, NO3

l = inside country, outside country

Then, country level averages will be computed as the weighted average of the iF of each plant located inside the country, using as the weight the power generation¹⁵ of each power plant.

¹⁵Using the average generation of each plant, the estimated generation according to (World Resources Institute 2018), or a simple average among plants when no generation data is available.

Finally, we calculate the changes in PM2.5 concentrations rearranging the terms in Equation 6.35, assuming that the entire population is exposed to the weighted average concentration. We also adjust the units to obtain changes in concentration in $\mu\text{g}/\text{m}^3$. CM corresponds to the implied “concentration matrix” that relates changes in concentration derived from 1 ton of emissions per year.

$$CM = \frac{\Delta C[\frac{\text{g}}{\text{m}^3}]}{1 [\text{tonne}/\text{year}]} = \frac{iF (\text{ppm})}{\text{BR} (\frac{\text{m}^3}{\text{d}}) * 365 (\frac{\text{d}}{\text{year}}) * \text{Pop} (\text{capita})} * 10^6 \quad (6.40)$$

Where ΔC is the change in ambient concentration of PM2.5, iF is a national level average intake fraction, BR is an average breathing rate and Pop is the country’s population.

6.5.6 Option 5: Machine learning

The user can also choose to use the results of a machine learning approach, developed for CPAT Renna and Reis (2021). The results of the model have been approximated using a discrete function, that relates emissions perturbations to total ambient concentrations of PM2.5 and O3.

$P_{s,p,t}$ is the perturbation compared to emissions in the baseline year, t_0 , in percentage. We use 2019 as the baseline year and all the perturbations are compared to that year, as presented in Equation 6.41.

$$P_{s,p,t} = \left(\frac{\text{Emissions}_{s,p,t}}{\text{Emissions}_{s,p,t_0}} - 1 \right) * 100 \quad (6.41)$$

Total ambient concentration is a function of $P_{s,p,t}$, composed of a set of linear relationships, according to the level of the perturbation, as presented in Equation 6.42.

$$C(P_{s,p,t}) = \begin{cases} \text{if } P_{s,p,t} < -100, & a_{-100} \\ \text{if } -100 \leq P_{s,p,t} < -80, & a_{-100} + b_{-100} * (P_{s,p,t} - (-100)) \\ \text{if } -80 \leq P_{s,p,t} < -60, & a_{-80} + b_{-80} * (P_{s,p,t} - (-80)) \\ \text{if } -60 \leq P_{s,p,t} < -40, & a_{-60} + b_{-60} * (P_{s,p,t} - (-60)) \\ \text{if } -40 \leq P_{s,p,t} < -20, & a_{-40} + b_{-40} * (P_{s,p,t} - (-40)) \\ \text{if } -20 \leq P_{s,p,t} < 0, & a_{-20} + b_{-20} * (P_{s,p,t} - (-20)) \\ \text{if } 0 \leq P_{s,p,t} < 20, & a_0 + b_0 * (P_{s,p,t} - 0) \\ \text{if } 20 \leq P_{s,p,t} < 40, & a_{20} + b_{20} * (P_{s,p,t} - 20) \\ \text{if } 40 \leq P_{s,p,t} < 60, & a_{40} + b_{40} * (P_{s,p,t} - 40) \\ \text{if } 60 \leq P_{s,p,t} < 80, & a_{60} + b_{60} * (P_{s,p,t} - 60) \\ \text{if } 80 \leq P_{s,p,t} < 100, & a_{80} + b_{80} * (P_{s,p,t} - 80) \\ \text{if } P_{s,p,t} > 100, & a_{100} + b_{100} * (P_{s,p,t} - 100) \end{cases} \quad (6.42)$$

For the baseline year t_0 , the contribution of sector s and pollutant p to ambient PM2.5 is presented in Equation 6.43. The mentioned contribution is equivalent to the change in ambient PM2.5 when the emissions are reduced to zero (a -100% perturbation).

$$C_{s,p,t_0} = -C_{s,p,t}(P_{s,p,t} = -100) \quad (6.43)$$

Then, the contribution in each year t of sector s and pollutant p to ambient PM2.5 is presented in Equation 6.44.

$$C_{s,p,t} = C_{s,p,t}(P_{s,p,t}) - \text{BaselineConcentration} + C_{s,p,t_0} \quad (6.44)$$

The change in contribution to ambient PM2.5 or Ozone is calculated by subtracting the contribution in the baseline and the contribution under the carbon policy scenario.

6.5.7 Option 6: Average between two methods

In addition to the options to relate emissions and concentrations described above, the user can select the average among two of the methods described: intake fractions (Section 6.5.5) and source-apportionment information combined with TM5-FASST method (Section 6.5.3). We added this option since every method used is subject to uncertainty and using more than one estimate will provide results in the middle range of different model estimates.

6.5.8 Modeled and total ambient pollution

In CPAT, we estimate emissions from the sectors and fuels presented in Table 6.2 according to the methodology described in Section 6.4. Then, using one of the six options described in Section 6.5, we determine the “modeled” ambient PM2.5 (or O3). The modeled concentration accounts only for fuel burning activities, but not for all ambient pollution.

Other sources of pollution (not fuel burning) include resuspended dust, sea salt, forest fires, or other transboundary sources that contribute to observed PM2.5. We assume that the sources not modeled in CPAT contribute a C_0 level to ambient pollution. We calculate the value C_0 for a baseline year, using Equation 6.45, and we assume it to remain constant across time.

$$\text{Observed } C_{t_0} = \text{Modeled } C_{t_0} + C_0 \quad (6.45)$$

Total ambient concentration each year t is modeled in CPAT using expression Equation 6.46.

$$\text{Ambient } C_t = \text{Modeled } C_t + C_0 \quad (6.46)$$

Figure 6.14 presents graphically the methodology applied: a constant C_0 and a modeled concentration that varies in time.

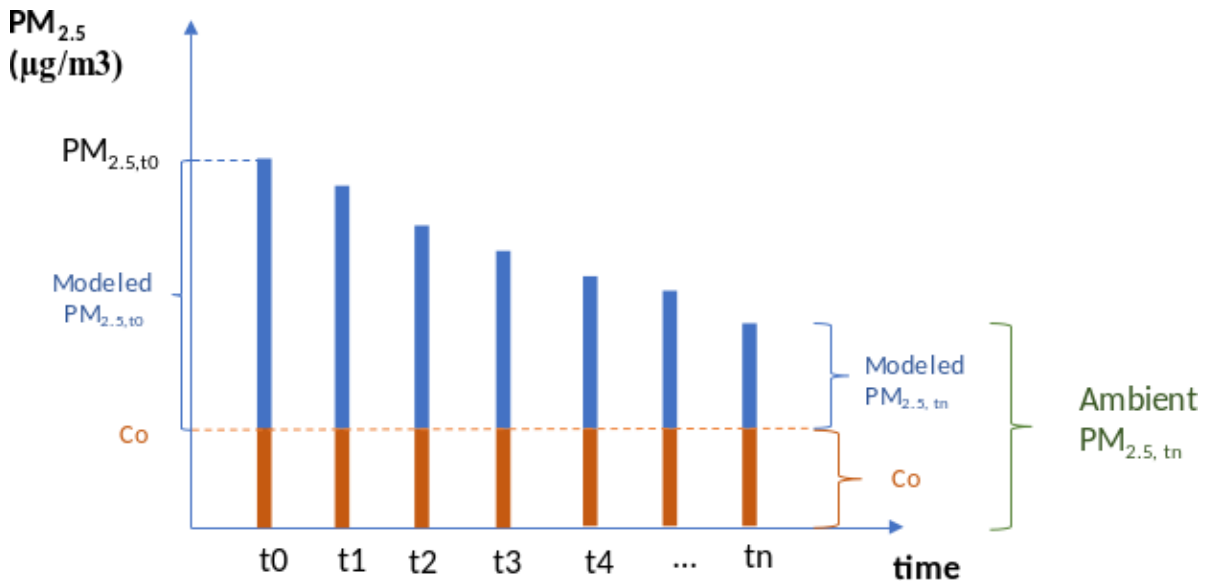


Figure 6.14: Illustrative example of the projection in time of ambient PM2.5 in CPAT

Source: Own elaboration

6.6 Methods to calculate the health burden of air pollution

This chapter describes the methodologies and data sources used to quantify the health impacts attributed to air pollution in CPAT. The health metrics described in this section, such as mortality, are the main result from the air pollution tab.

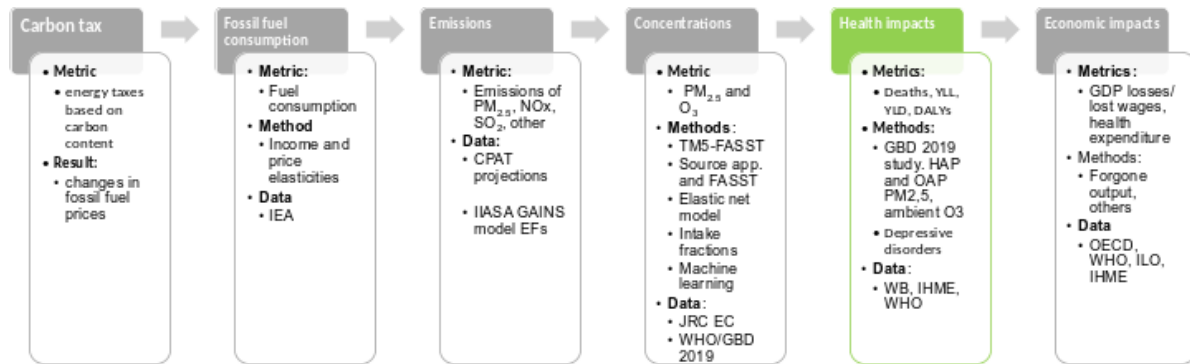


Figure 6.15: Health effects, CPAT methodology overview

Source: Own elaboration

The health burden of air pollution is quantified using the methodology illustrated in Figure 6.16. The health outcomes included in CPAT are premature mortality and disability-adjusted life years (DALYs), explained in the following sections.

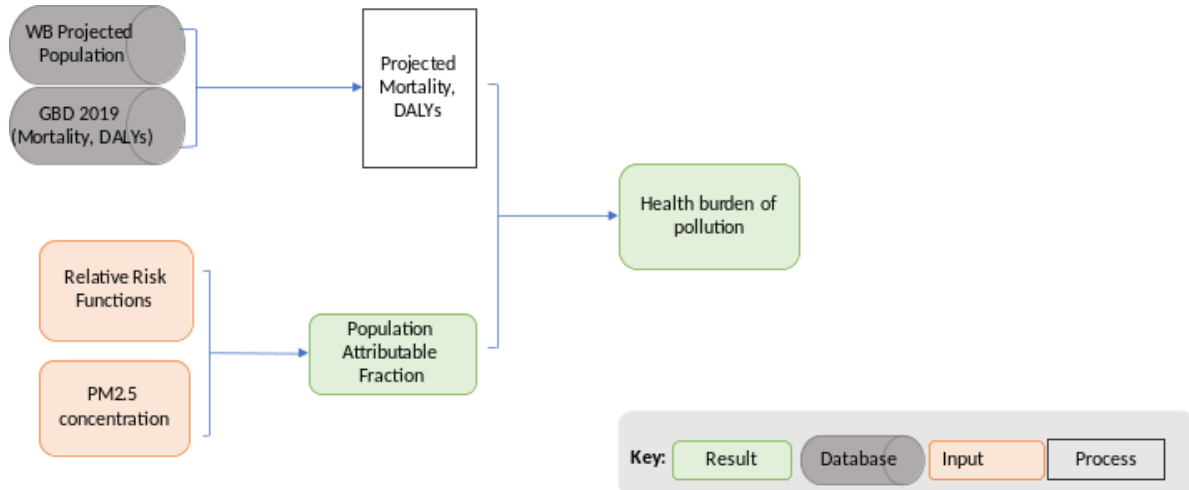


Figure 6.16: Methodology for estimating the health burden of pollution

Source: Own elaboration

6.6.1 Data sources to estimate health impacts

Input

Source

Relative Risk estimates (by cause, age and exposure level)

Global Burden of Disease Health Financing Collaborator Network (2020)

Population projections by age group and country

WB Population Estimates and Projections¹⁶. The database includes population projections by country, sex and age range by country up to 2050. It also includes the share of urban and rural populations.

Urban population fraction by country

World Bank Group

Mortality and DALYs

Global Burden of Disease Health Financing Collaborator Network (2020) Mortality and DALYs for:

Ischemic heart disease

Chronic obstructive pulmonary disease

Lower respiratory infections

Stroke

Tracheal, bronchus, and lung cancer

Diabetes mellitus type II

Neonatal diseases: Sudden infant death syndrome, Diarrheal diseases, Lower respiratory infections, Upper respiratory infections, Otitis media, Meningitis, Neonatal disorders, Encephalitis

Exposure to ambient PM2.5

WHO Country average exposure (World Health Organization (2018a))¹⁷ and Global Burden of Disease Health Financing Collaborator Network (2020) ambient concentrations.

Exposure to indoors PM2.5

Data from the Global Burden of Disease Health Financing Collaborator Network (2020) study, provided by Michael Brauer

¹⁶Data available in <https://datacatalog.worldbank.org/dataset/population-estimates-and-projections>

¹⁷Data available in <http://apps.who.int/gho/data/node.main.152?lang=en>

Exposure to ozone pollution

Data from the Global Burden of Disease Health Financing Collaborator Network (2020) study, provided by Michael Brauer

6.6.2 Definitions of key technical terms

Relative Risk (RR) is a measure of the change in risk of an adverse health effect associated with an increase in air pollution levels. RR indicates the likelihood of developing the disease of effect in the exposed group, relative to those who are not exposed.

$$RR = \frac{y_0}{y_c} \quad (6.47)$$

Where:

y_0 : the risk (or probability) that people with baseline pollutant exposure will be adversely affected

y_c : the risk (or probability) that people with control pollutant exposure will be negatively affected.

For example, a RR for all-cause mortality equal to 1.03 per 10 $\mu\text{g}/\text{m}^3$ increase in annual PM2.5 means that a 10 $\mu\text{g}/\text{m}^3$ increase in PM2.5 is associated with a 3% increase in deaths from all causes.

Hazard represents an instantaneous event rate or the probability that an individual would experience an event at a given point in time.

Hazard Ratio is defined as the baseline hazard (H_0) divided by hazard in the control group (H_c).

$$HR = \frac{H_0}{H_c}$$

Hazard ratio is often interpreted as relative risk, but they are not technically the same. The main difference is that relative risk does not consider the timing of the event but only the occurrence of the event by the end of the observation period. The hazard ratio considers both.

Incidence corresponds to the number of new cases of a given disease during a given period in a specified population. It also is used for the rate at which new events occur in a defined population. It is differentiated from prevalence, which refers to all cases, new or old, in the population at a given time¹⁸.

¹⁸Reference from <https://www.healthdata.org/terms-defined>

$$\text{Incidence proportion} = \frac{\text{number of new cases in period}}{\text{population at the start of the period}} * 10^5$$

Prevalence is the total number of cases of a given disease in a specified population at a designated time. It is differentiated from incidence, which refers to the number of new cases in the population at a given time¹⁹.

$$\text{Period Prevalence} = \frac{\text{number of prevalent cases in period}}{\text{number of individuals in period}} * 10^5$$

The population attributable fraction (PAF) is the reduction in incidence that would be observed if the population were entirely unexposed, compared with its current exposure pattern. In other words, PAF is the portion of the incidence that could be reduced if causative exposure were eliminated

6.6.3 The health burden of pollution

The burden of disease associated with air pollution estimates the reduction in specific causes of death that would occur if the exposure were reduced to an alternative level (in general, the theoretical minimum risk level is used). The methodology combines information regarding population exposure to ambient air pollution and an exposure-response relationship.

Source: World Health Organization and others (2018)

In CPAT, we implemented a method to assess jointly indoors and outdoors pollution as described in Section 6.6.4.1. CPAT also calculates the impacts of ozone pollution, as described in Section 6.6.4.3.

6.6.3.1 Joint ambient and household air pollution (Global Burden of Disease Health Financing Collaborator Network (2020))

In CPAT, we quantify the effects of air pollution following the methodology of the Global Burden of disease study for 2019 (Global Burden of Disease Health Financing Collaborator Network (2020)). The methodology uses and Integrated Exposure Response (IER) approach, basing its estimates in studies for ambient pollution, second-hand smoking and household pollution. This methodology represents and upgrade from the previous version of the study and the main differences with the previous methodology are the following:

- Global Burden of Disease Health Financing Collaborator Network (2020) no longer uses active smoking data in the risk curves. This removes an important source of uncertainty

¹⁹Reference from <https://www.healthdata.org/terms-defined>

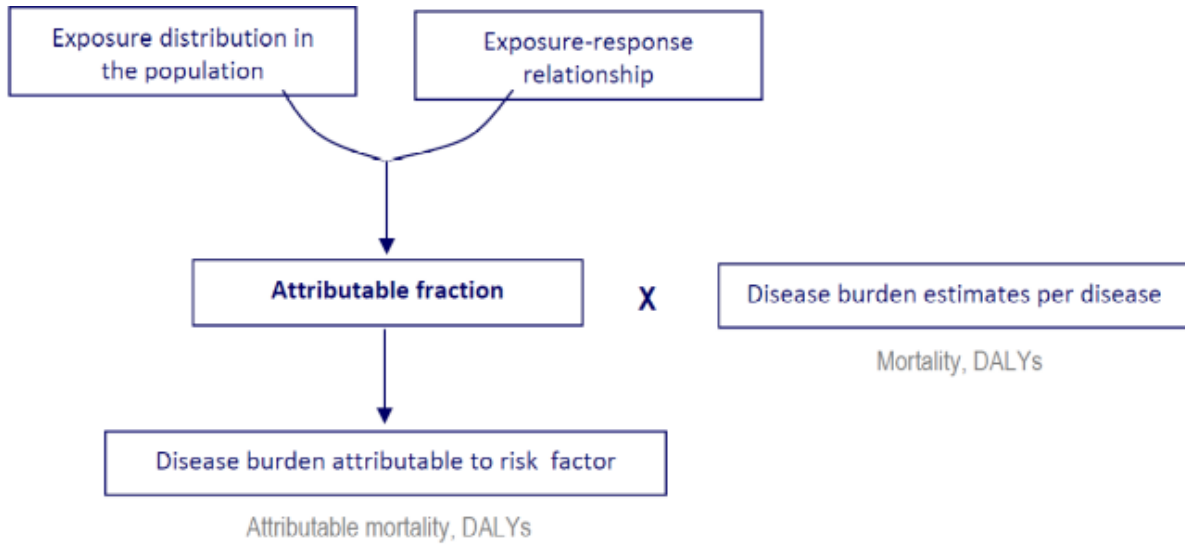


Figure 1: Method for burden of disease estimation. DALYs: disease adjusted life years.

Figure 6.17: Method for burden of disease estimation

- New studies in China and other high-exposure settings are now used²⁰
- No fixed functional form. Splines generated using MR-BRT (meta-regression boosted regression trees)

The methodology implemented in CPAT assess jointly the effects of ambient and household pollution. This feature is important because it allows the quantification of a possible increase in the use of solid fuels for cooking (leakage effects) and because household pollution is a major health problem in many countries of the world.

The relative risks used in CPAT from Global Burden of Disease Health Financing Collaborator Network (2020) are presented in Figure 6.18. In the case of ischemic heart disease and stroke, the RR presented is an average across all the age groups, which are defined in buckets of 5 years²¹. In CPAT, we work with the following age groups: neonates, post neonates, under 15, 15 to 64 and 65 years and above. We use the average relative risk within each group.

Notice that the relative risk takes as a reference the minimum risk level for PM_{2.5}, TMREL, defined as uniform distribution between 2.4 and 5.9 $\mu\text{g}/\text{m}^3$. In CPAT, we use as the TMREL the average between 2.4 and 5.9, equal to 4.15 $\mu\text{g}/\text{m}^3$ of PM_{2.5}. When pollution is below that level, we would obtain zero health effects attributed to pollution.

²⁰The new studies for China are (Yin et al. 2017) and (Li et al. 2018).

²¹The age groups with different RR for Stroke and Ischemic heart disease are: 25 to 29, 30 to 34, 35 to 39, 40 to 44, 45 to 49, 50 to 54, 55 to 59, 60 to 64, 65 to 69, 70 to 74, 75 to 79, 80 to 84, 85 to 89, 90 to 94, 95+.

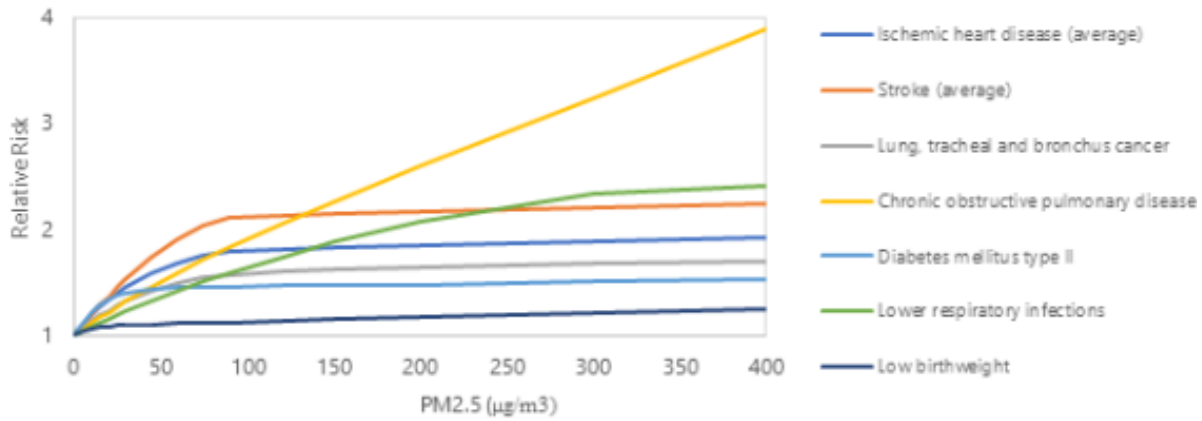


Figure 6.18: RR from the Integrated exposure response function, Global Burden of Disease Health Financing Collaborator Network (2020)

The diseases and age groups covered by the methodology in CPAT are presented in Table 6.13.

Table 6.13: Integrated Exposure Response function diseases from GBD 2019 implemented in CPAT

Cause	Age Group	RR
Chronic obstructive pulmonary disease	All ages	Constant across age groups
Diabetes mellitus type 2	All ages	
Lower respiratory infections	All ages	
Tracheal, bronchus, and lung cancer	All ages	
Ischemic heart disease	Above 25	Changes with age
Stroke	Above 25	
Low birthweight diseases ^{22, 23} , excluding lower respiratory infections	Neonatal (under 28 days)	Constant

Source: Own elaboration. Note: GBD2019 also quantifies preterm birth²⁴ effects attributed

²²Low birthweight is been historically referred to any birthweight less than 2500 grams. TMREL \$3500, 4000) g.

²³Low birthweight is a risk. The causes associated with this risk are Diarrheal diseases, Lower respiratory infections, Upper respiratory infections, Otitis media, Pneumococcal meningitis, H influenzae type B meningitis, Meningococcal meningitis, Other meningitis, Encephalitis, Neonatal preterm birth complications, Neonatal encephalopathy due to birth asphyxia and trauma, Neonatal sepsis and other neonatal infections, Haemolytic disease and other neonatal jaundice, Other neonatal disorders and Sudden infant death syndrome.

²⁴Preterm birth refers to newborn babies born less than 37 completed weeks of gestation. In the GBD context, “short gestation” is used to refer to all gestational ages below the gestational age TMREL. TMREL is \$38, 40) weeks.

to pollution. We do not quantify this in CPAT, to avoid double counting of effects, when aggregating the total impacts of pollution.

The joint methodology requires the fraction of the population that it is exposed to solid fuels for cooking, p_{HAP} , and the level of exposure to household air pollution (HAP), as the additional exposure over and above ambient exposure to PM2.5 (OAP).

For the proportion of the population **not** exposed to HAP, the relative risk is presented in Equation 6.48.

$$RR_{\text{OAP}} = MRBRT(z = \text{Exp}_{\text{OAP}}) / MRBRT(z = TMREL) \quad (6.48)$$

For the proportion of the population exposed to HAP, the relative risk is given by Equation 6.49.

$$RR_{\text{HAP}} = MRBRT(z = \text{Exp}_{\text{OAP}} + \text{Exp}_{\text{HAP}}) / MRBRT(z = TMREL) \quad (6.49)$$

The population level relative risk RR_{PM} and population attributable fraction, PAF_{PM} , are calculated according to Equation 6.50 and Equation 6.51.

$$RR_{\text{PM}} = RR_{\text{OAP}} * (1 - p_{\text{HAP}}) + RR_{\text{HAP}} * p_{\text{HAP}} \quad (6.50)$$

$$PAF_{\text{PM}} = 1 - 1/RR_{\text{PM}} \quad (6.51)$$

Finally, PAFs are split based on the exposure to OAP and HAP, as presented in Equation 6.52 and Equation 6.53.

$$PAF_{\text{OAP}} = \frac{\text{Exp}_{\text{OAP}}}{\text{Exp}_{\text{OAP}} + p_{\text{HAP}} * \text{Exp}_{\text{HAP}}} * PAF_{\text{PM}} \quad (6.52)$$

$$PAF_{\text{HAP}} = \frac{p_{\text{HAP}} * \text{Exp}_{\text{HAP}}}{\text{Exp}_{\text{OAP}} + p_{\text{HAP}} * \text{Exp}_{\text{HAP}}} * PAF_{\text{PM}} \quad (6.53)$$

Notice that under this strategy $PAF_{\text{PM}} = PAF_{\text{HAP}} + PAF_{\text{OAP}}$.

Where:

Exp_{OAP} : Ambient PM2.5 exposure level

Exp_{HAP} : Excess exposure to PM2.5 for those who use solid fuel for cooking.

p_{HAP} : proportion of the population using solid fuel for cooking

RR_{OAP} : Relative risk for the proportion of the population **not** exposed to HAP

RR_{HAP} : Relative risk for the proportion of the population exposed to HAP

RR_{PM} : Population level relative risk

PAF_{PM} : Population level PAF

Figure 6.19 presents a diagram of the exposure to $PM_{2.5}$, Exp_{OAP} and Exp_{HAP} , and their associated relative risks levels.

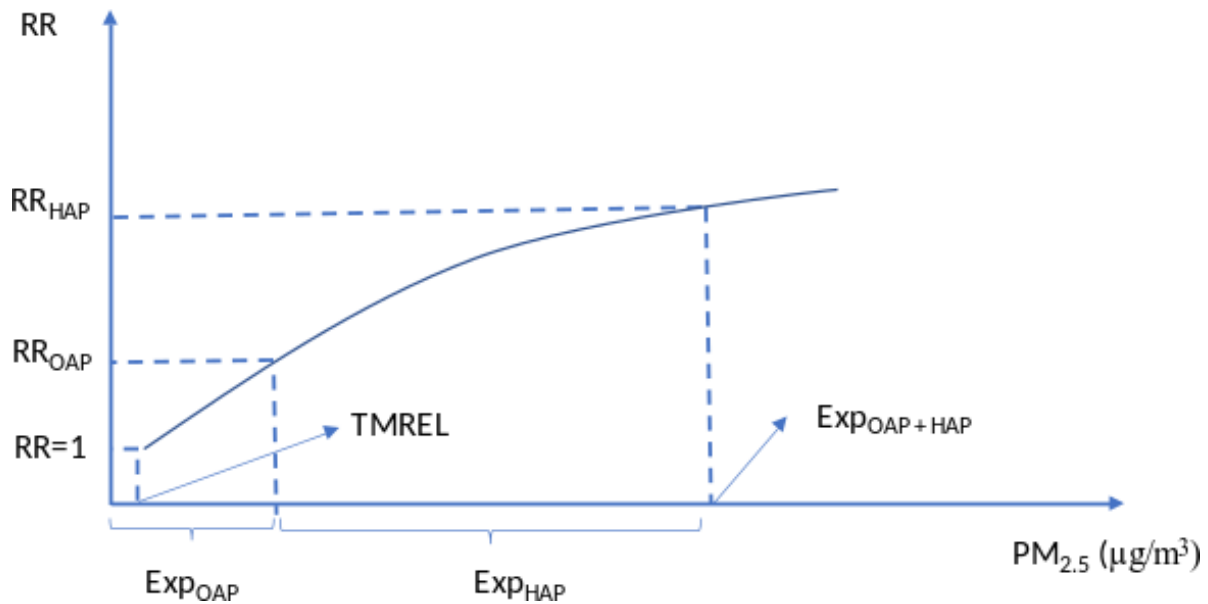


Figure 6.19: Diagram for relative risk due to HAP and OAP exposure

Source: Own elaboration

The Attributable burden (AB) corresponds to the number of cases attributed to the exposure in the population. The AB is calculated by multiplying PAF by the baseline number of health outcomes, for each outcome, sex and age group.

$$AB = PAF * Health\ Outcome$$

The strategy to quantify health effects in CPAT is presented in Section 6.10.3.

6.6.3.2 Health outcomes in CPAT

In CPAT, we quantify the health effects of pollution as mortality, years of life lost, years lived with disability and disability-adjusted life years (DALYs).

DALY is a summary measure which combines time lost through premature death and time lived in states of less-than-optimal health or “disability”. Figure 6.20 presents an infographic about the DALY metric.

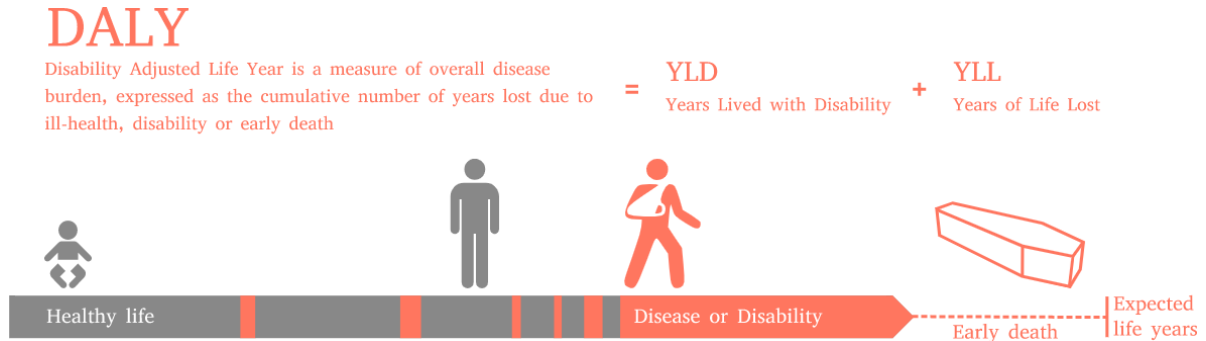


Figure 6.20: DALY or disability-adjusted life year infographic

Source: Wikimedia Commons contributors (2020)

DALY, for a specific cause c , sex s , age a and year t is defined as indicated in Equation 6.54.

$$\text{DALY}_{c,s,a,t} = \text{YLL}_{c,s, a,t} + \text{YLD}_{c,s,a,t} \quad (6.54)$$

The years of life lost (YLL) are calculated in Equation 6.55 as the number of deaths multiplied by a loss function specifying the years lost for deaths as a function of the age at which death occurs.

$$\text{YLL}_{c,s, a,t} = \text{Number of deaths}_{c,s,a,t} * L_{s,a} \quad (6.55)$$

Where $L_{s,a}$ is a standard loss function specifying years of life lost for a death at age a for sex s .

The years lived with disease (YLD) are measured by the multiplication of the prevalence of the condition²⁵ and a weight factor that reflects the severity of the condition on a scale from 0 (perfect health) to 1 (death) as expressed in Equation 6.56.

$$\text{YLD}_{c,s,a,t} = P_{c,s,a,t} * \text{DW}_{c,s,a} \quad (6.56)$$

Where,

$P_{c,s,a,t}$: Prevalent sequelae for cause c , sex s , age a and year t

$\text{DW}_{c,s,a}$: Disability weight for sequelae for cause c , sex s and age a

²⁵The WHO considers sequelae associated to different diseases or conditions.

CPAT uses incidence at a country level for DALYs, YLL and YLD from Global Burden of Disease Health Financing Collaborator Network (2020).

6.6.3.3 Ozone air pollution

For ozone health effects, CPAT follows the methodology applied in Global Burden of Disease Health Financing Collaborator Network (2020), which is based on Turner et al. (2016). The health impacts are quantified for chronic obstructive pulmonary disease, with a RR of 1.06 (1.02, 1.10) per 10 ppb of ozone, in the seasonal (six-month period with the highest mean) 8-h daily maximum concentration metric (6mDMA8h). The TMREL for ozone is defined as $\sim U(29.1, 35.7)$.

The relative risk is represented by expression Equation 6.57 and PAF is calculated using expression Equation 6.58.

$$RR = e^{\beta * C_{O_3}} \quad (6.57)$$

$$PAF = 1 - e^{-\beta * C_{O_3}} \quad (6.58)$$

The change in ozone concentration C_{O_3} is obtained using the diagonal source-receptor coefficients from TM5-FASST, adjusted from region level to countries using Equation 6.3, from Section 6.5.2; or the “machine learning” model for ozone from Section 6.5.6.

Precursors of ozone considered in CPAT are NO_x, NMVOC, SO₂ and CH₄.

6.6.3.4 Multiple risks factors

When multiple risks affect the same outcome, we need to apply a multiplicative aggregation of each individual risk, according to Equation 6.59.

$$PAF_{1..i} = 1 - \prod_{i=1}^n (1 - PAF_i) \quad (6.59)$$

Where i corresponds to each individual risk factor.

In CPAT, COPD is the only health outcome associated to two different risks (O₃ and PM_{2.5} pollution). Equation 6.60 presents the “corrected” PAF to consider the two risks factors, when aggregating the individual risks.

$$PAF_{MP2.5-O_3-COPD} = 1 - (1 - PAF_{PM2.5}) * (1 - PAF_{O_3}) \quad (6.60)$$

We apply the correction for multiple risks only when we need to add up the effects of PM2.5 and O3. In CPAT, this is done only when valuing (using VSL) total averted mortality.

The correction factor is calculated using Equation 6.61.

$$\text{Corr}_{\text{factor}} = \frac{\text{PAF}_{\text{MP2.5-O3-COPD}}}{\text{PAF}_{\text{PM2.5}} + \text{PAF}_{\text{O3}}} \quad (6.61)$$

Adjusted total deaths attributed to PM2.5 and Ozone are calculated by multiplying the $\text{corr}_{\text{fact}}$ by the unadjusted O3 and PM2.5 attributed deaths.

6.6.4 Baseline exposure to air pollution data

6.6.4.1 Ambient PM2.5 Exposure data

CPAT will use population weighted average PM2.5 concentrations. In WHO databases, average concentrations are available for rural and urban areas for each country. In most countries, urban populations, in average, are exposed to higher levels of ambient PM2.5. Figure 6.21 presents an example of urban and rural PM2.5 for a group of countries.

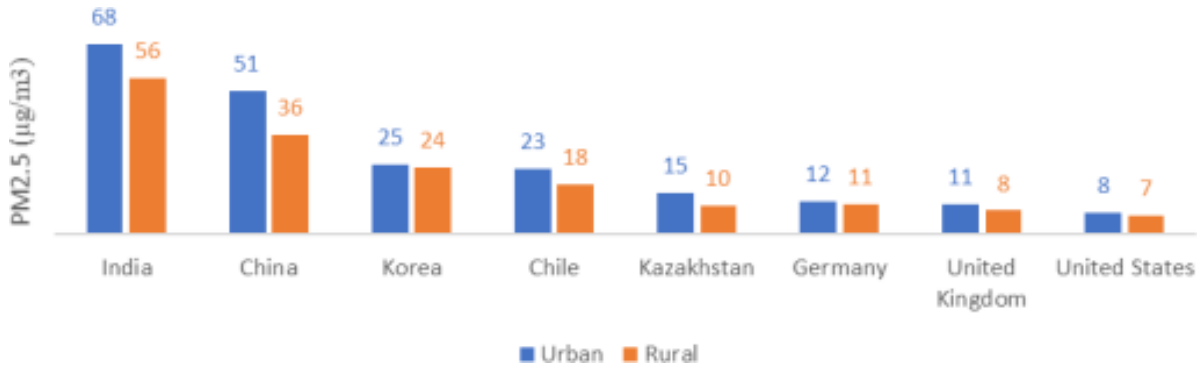


Figure 6.21: Example of urban and rural weighted average concentrations

Source: World Health Organization and others (2018)

In CPAT, we also use the estimations of ambient PM2.5 from the Global Burden of Disease Health Financing Collaborator Network (2020) study. We assume the same ratio between urban and rural concentrations levels from World Health Organization (2018a) and the overall concentrations from Global Burden of Disease Health Financing Collaborator Network (2020). Figure 6.22 presents the gridded values for ambient PM2.5 in 2019.

Source: Own elaboration, based on Institute for Health Metrics and Evaluation (IHME) (2020) data

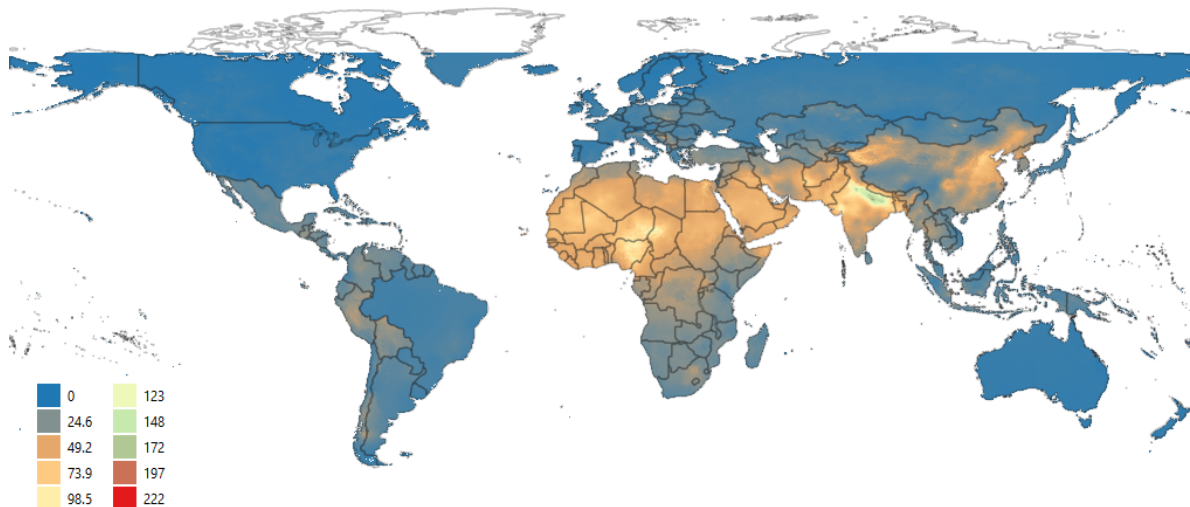


Figure 6.22: Gridded mean of PM2.5, year 2019

6.6.4.2 Household PM2.5 Exposure data

As we mentioned before, in CPAT we estimate jointly the impacts of ambient and household pollution. To do so, we need to know the share of the population exposed to household pollution and the exposure level to household PM2.5. We again draw upon data from the Global Burden of Disease Health Financing Collaborator Network (2020) study.

The left panel in Figure 6.23 shows the estimated evolution in the share of the population exposed to household pollution in time, while the right panel presents the exposure level, in addition to the OAP exposure, for the World Bank regions. For the baseline scenario, we assume that the share of the population exposed, and the exposure level will be constant in time, and equal to the estimated value for 2019.

Source: IHME/GBD, provided by Michel Brauer

6.6.4.3 Ozone Exposure data

As mentioned before, we use the seasonal 8 hours maximum daily value to estimate the health effects of ambient ozone pollution. Figure 6.24 presents the gridded concentrations estimated for 2019.

Source: Own elaboration, based on data provided by Michael Brauer

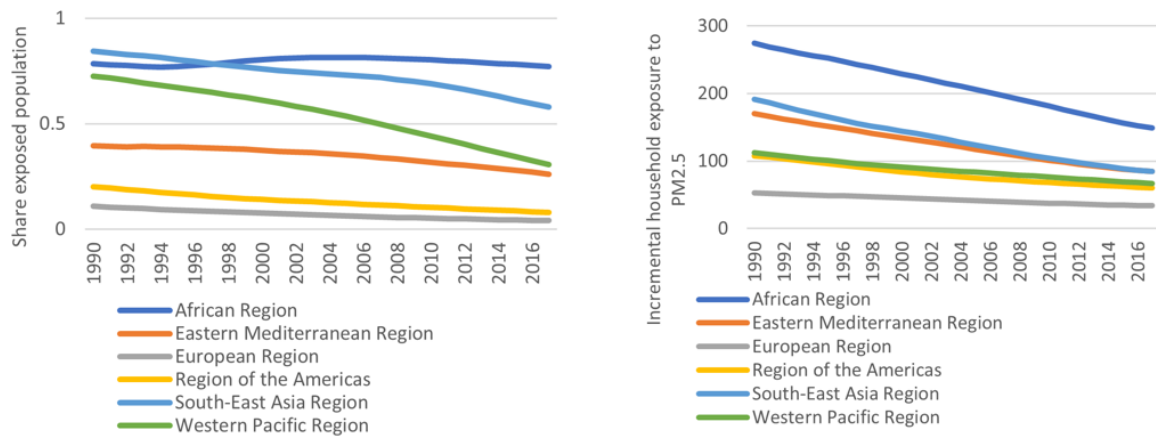


Figure 6.23: Share of the population (left) and level of additional population (right) exposed to households air pollution

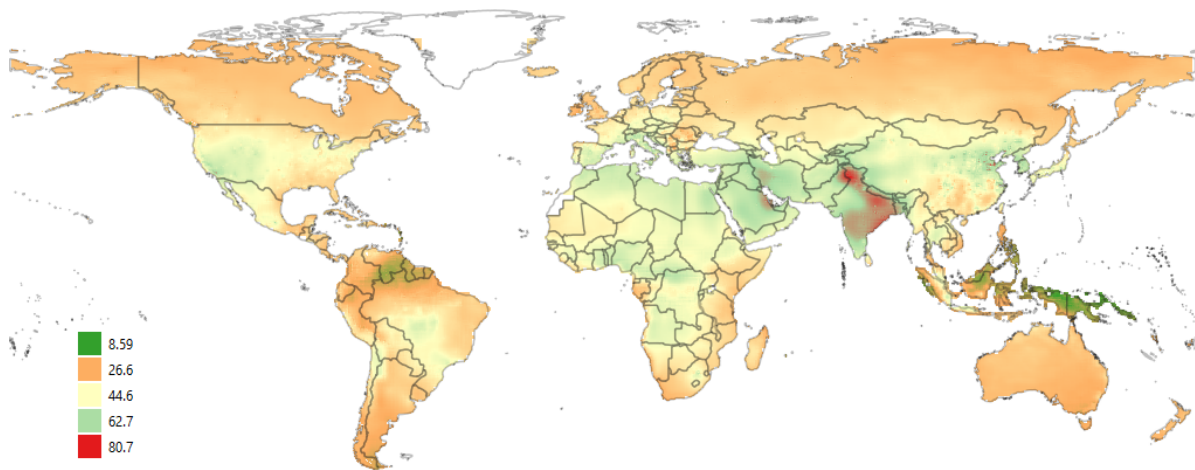


Figure 6.24: Gridded concentrations of O3, year 2019 (6mDMA8h)

6.6.5 Leakage to biomass

Carbon pricing to formal fuels could potentially lead to an increase in the use of solid fuels²⁶ for cooking. This is called a “leakage” effect and could increase both household and ambient pollution. Figure 6.25 illustrates the carbon pricing effects on fuels consumption.



Figure 6.25: Illustration of the impact on carbon pricing in the consumption of fuels

Source: Own elaboration

The demand for fuels, including the demand for biomass for cooking is calculated in the Mitigation tab in CPAT. For details on energy demand calculations, please refer to the Mitigation tab documentation.

As illustrated in Figure 6.25, the leakage into informal fuels could increase the proportion of households exposed to HAP, the level of exposure to HAP and OAP. The assumption for OAP is that 100% of indoor emissions are eventually incorporated into ambient air (Chafe et al. (2014)). These ambient emissions are converted into ambient pollution using the methodology selected by the user, as described in Section 6.5.

Regarding the indoors effect of solid fuel use, the total leakage is divided in a fraction that increases the proportion of households and a fraction that increases the level of household pollution.

In CPAT, the default assumptions are that 50% of the increase in informal fuels consumption goes to additional household consuming solid fuels and 50% to increased consumption within households that were already using solid fuels.

In many countries is estimated that 90% of households or more use solid fuels for cooking. To make sure that the final proportion of households that uses solid fuels for cooking, after leakage is considered, is less than 100% (or another maximum value defined by the user), we adjust the fraction of the leakage that goes into the proportion of households. Equation 6.62 corresponds to the final proportion of households that uses solid fuels for cooking before adjustments. Equation 6.63 is the adjusted fraction in case the new share of households using solid fuels is

²⁶Solid fuels include coal, wood, charcoal, dung, and agricultural residues.

higher than the maximum defined. Equation 6.64 is the final proportion of households using solid fuels for cooking.

$$\text{ProportionHH}_{\text{carbon price}} = \text{ProportionHH}_{\text{baseline}} * (1 + \text{Leakage} * F_{\text{propHH}}) \quad (6.62)$$

$$F_{\text{prop_HH}}_{\text{adjusted}} = \left(\frac{\text{MaxPropHH}}{\text{ProportionHH}_{\text{baseline}}} - 1 \right) * \frac{1}{\text{Leakage}} \quad (6.63)$$

$$F_{\text{prop_HH}} = \begin{cases} \text{if } \text{ProportionHH}_{\text{carbon price}} > \text{Max then } F_{\text{prop_HH}}_{\text{adjusted}} \\ \text{else } \text{ProportionHH}_{\text{carbon price}} \end{cases} \quad (6.64)$$

6.6.6 Other health effects in CPAT

6.6.6.1 Post neonatal mortality (Woodruff, Parker, and Schoendorf (2006))

In CPAT, it is possible to quantify post neonatal mortality (deaths after the first month and up to 1 year of life) using Woodruff, Parker, and Schoendorf (2006). This logistic function is presented in Equation 6.65, its applied to ambient PM2.5, to all-cause mortality and its parameters are $\beta = 0.006765865$, with $\sigma = 0.007338828$.

$$\left(1 - \left(\frac{1}{(1 - \text{Incidence}) * \text{EXP}(\beta * \text{Delta}Q) + \text{Incidence}} \right) \right) * \text{Incidence} * \text{POP} \quad (6.65)$$

6.6.6.2 Depressive disorders

Another effect of ambient air pollution included in CPAT is depressive disorders. Braithwaite et al. (2019) develops a meta-analysis of studies linking long-term PM exposure and depression. The author develops a log-linear exposure-response function and uses a counterfactual value of 10 $\mu\text{g}/\text{m}^3$ for the UK and of 25 $\mu\text{g}/\text{m}^3$ for global scenario. In the meta-analysis, the pooled odds ratio for the association between long-term PM2.5 exposure and depression prevalence obtained was 1.102 per 10 $\mu\text{g}/\text{m}^3$ (95% CI: 1.023, 1.189; p=0:011), indicating that higher PM2.5 exposure is associated with higher odds of depression.

They treat pooled ORs as equivalent to RRs. The relative risk can be calculated according to Equation 6.66.

$$RR \approx \text{OR}_{10} * \frac{PM2.5_{\text{current}} - PM2.5_{\text{counterfactual}}}{10} \quad (6.66)$$

Where OR_{10} denotes the OR per 10 $\mu\text{g}/\text{m}^3$ increment in $\text{PM}_{2.5}$ exposure.

In CPAT, the counterfactual level, $\text{PM}_{2.5}_{\text{counterfactual}}$ used is 25 $\mu\text{g}/\text{m}^3$.

6.7 Methods to quantify the economic impacts of air pollution

In this section we describe the economic impacts of pollution included in CPAT. The metrics included are working days lost due to pollution, output losses due to mortality and morbidity, and health expenditure. We also explain how we value averted mortality, using a transferred VSL, the time structure of averted deaths and the valuation of travel time saved (used in CPAT Transport tab).

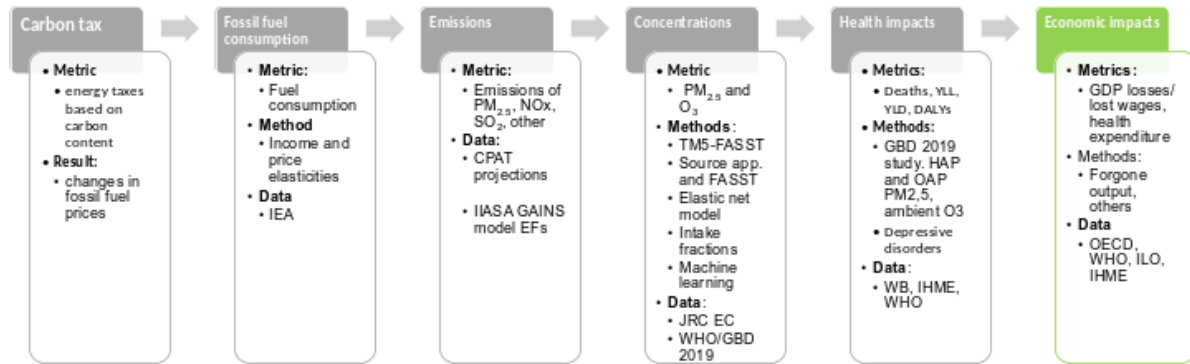


Figure 6.26: Economic impacts, CPAT methodology overview

6.7.1 Data sources used to quantify economic impacts

Table 6.14: Summary of data sources used to quantify economic impacts of pollution

Input	Source
Absenteeism from work	OECD (2021b), World Bank (2019b)
Methodology for working days lost	Ostro (1987), Holland (2014), ECLIPSE V5a Global Emission Fields - Global Emissions (2015)
Methodology for productivity losses	Personal communications with Maureen Cropper
Labor's share of GDP	Guerriero (2019)
Employment to population ratio, unemployment, wages, growth rate of GDP per worker	ILOs indicators

Input	Source
Real interest rate ²⁷	World Development Indicators, World Bank
Health expenditure methodology Data on health expenditure	Preker et al. (2016) Global Burden of Disease Health Financing Collaborator Network (2019b)
VSL	OECD (2012), Narain and Sall (2016), OECD (2021a) and OECD (2021b)
Time structure of averted deaths	US EPA (2013)
Travel time saved	International Road Federation (2018a), Robinson, Hammitt, and O’Keeffe (2019), Tomtom’s data.

6.7.2 Working days lost

Work absenteeism has direct costs because of wage losses and replacement costs, and indirect costs in productivity, due to delayed work and possible interference with the work performed by co-workers and supervisors.

Source: OECD (2020) and WHO (2019)

In CPAT, we quantify working days lost attributed to pollution following Ostro (1987). This methodology has been implemented in more recent literature, such as Holland (2014) and Amann et al. (2017). OECD research OECD (2016) and OECD (2019) has also been based indirectly in Ostro (1987) but referencing the work from Holland (2014).

The baseline absenteeism from work due to illness data used are the OECD database “Absence from work due to illness” (OECD (2020)) that covers 46 countries²⁸ and “Absenteeism from work due to illness”²⁹ from the WHO (2019). Figure 6.27 presents the data from the observed databases.

Since not every country is covered in the databases, we adopt the following assumptions for obtaining baseline absenteeism at a country level:

- If the country is included in the OECD database, we use OECD data.
- If no OECD data is available, but WHO data includes the country, we use WHO adjusted by “employment to total population ratio, 15+” (ILO n.d.).

²⁷Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator.

²⁸Data available in <https://stats.oecd.org/index.aspx?queryid=30123>

²⁹Data available in https://gateway.euro.who.int/en/indicators/hfa_411-2700-absenteeism-from-work-due-to-illness-days-per-employee-per-year/

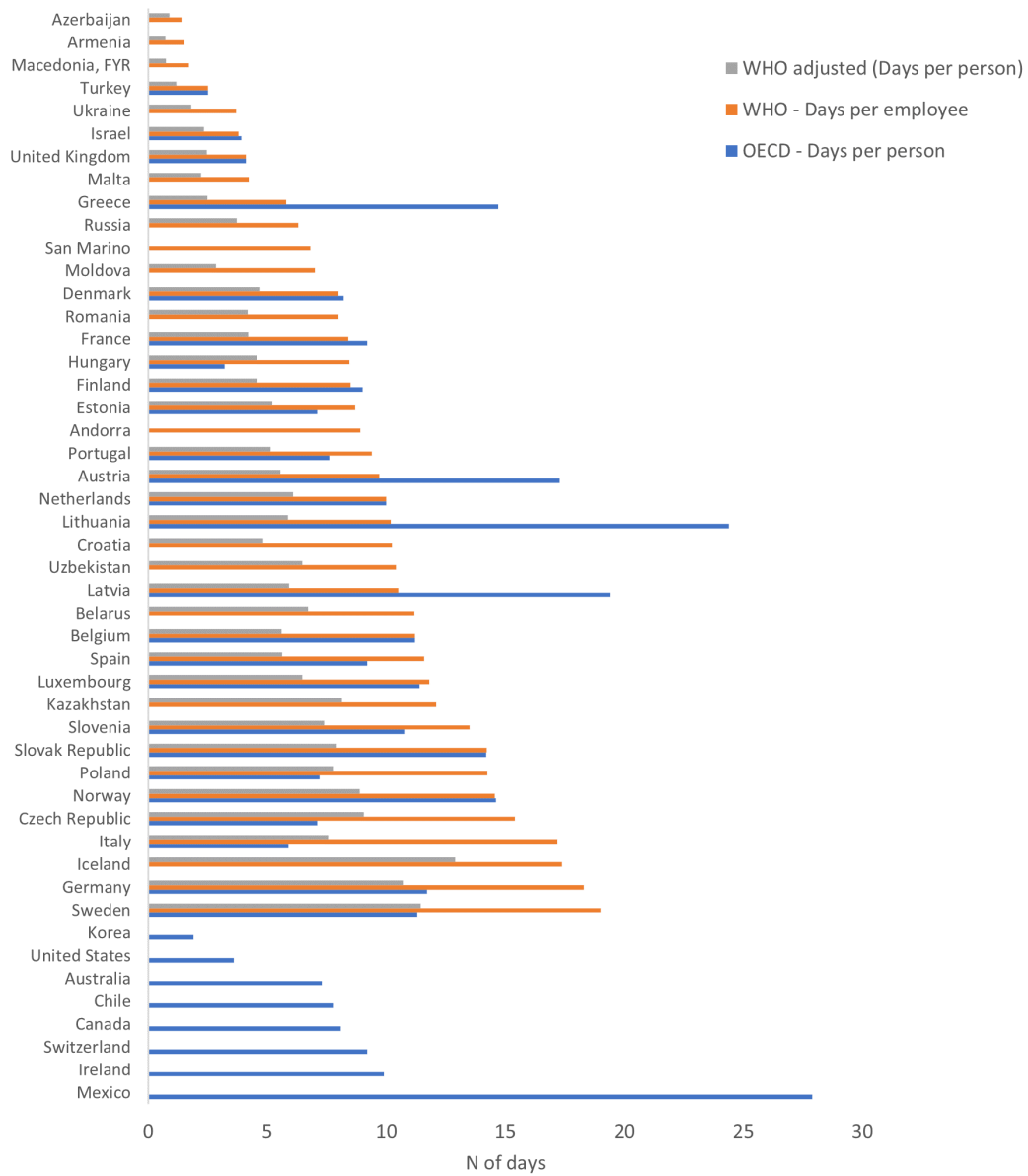


Figure 6.27: Work absenteeism due to illness

- If no country specific data is available, we use the average value among countries with the same income level.
- For low-income countries (that are not represented in either database), we use the average from lower middle-income countries.

To calculate the share of work absenteeism due to illness that can be attributed to ambient PM2.5 pollution, we use the methodology from Ostro (1987). The study developed a log-linear function with $\beta = 0.0046$ and $\sigma_\beta = 0.00036$. The attributable fraction of working days lost due to pollution is calculated using Equation 6.67 and the total number of days lost due to pollution is given by Equation 6.68.

$$PAF = 1 - e^{-\beta * C} \quad (6.67)$$

$$WDL_{\text{pollution}} = \text{Pop}_{15 \text{ to } 64} * \text{Per person } WDL_{\text{baseline}} * (1 - e^{-\beta * C \text{ baseline}}) \quad (6.68)$$

Where ΔC is the current level of PM2.5 minus a reference level for PM2.5, that is assumed to be 0 in this case.

To value the days of work lost due to pollution, we use mean monthly earnings of employees, ILOSTAT Labor statistics.

If no wage is available, the default value used is:

$$\text{Daily wage} = \frac{GDP * \alpha}{N^\circ \text{ of persons employed}} * \frac{1}{N^\circ \text{ of days}} \quad (6.69)$$

Where $N^\circ \text{ of days} = 12 * 20$.

We consider working population from 15 to 64 years old, as in Amann et al. (2017).

6.7.3 Market output losses

In CPAT, we quantify market output losses using mortality and years lived with disability (YLD) attributed to pollution, following the methodology in Pandey et al. (2021). The methodology followed is presented in the following paragraphs.

Average GDP contribution by worker

Equation 6.70 presents the expected value of GDP per worker in a given year, that we will use to quantify GDP losses due to pollution.

$$W_{ij} = \left(\frac{L_{ij}}{N_{ij}} \right) \left(\frac{Y_i}{L_i} \right) \quad (6.70)$$

Where:

W_{ij} : the expected value of GDP per worker for a person of age j in state i .

α : Labor's share of GDP

Y_i : GDP

L_i : number of persons who are employed

N_{ij} : Population of age j in state i

Due to data limitations, in CPAT will compute a value W for every worker above 15+, without differentiating by age or by urban and rural areas.

For each period (year) p , the expected GDP from labor per person is calculated using Equation 6.71.

$$W_p = \left(\frac{L_p}{N_p} \right) \left(\frac{Y_p}{L_p} \right) = \frac{Y_p}{N_p} \quad (6.71)$$

Loss in market and non-market output due to air pollution mortality

Losses in market and non-market output due to air pollution mortality can be estimated according to Equation 6.72.

$$W'_{ij2017} = \left(\frac{L_{ij}}{N_{ij}} \right) \left(\frac{Y_i}{L_i} \right) + hp \left(1 - \frac{L_{ij}}{N_{ij}} \right) \left(\frac{Y_i}{L_i} \right) \quad (6.72)$$

Where hp represents household production. In CPAT, due to data limitations, we will only include losses in market output.

The present value of the forgone output associated to a premature death is calculated according to Equation 6.73.

$$PV_{ij} = \sum_{a=j}^{84} \pi_{ij,t} \left[\left(\frac{L_{it}}{N_{it}} \right) \left(\frac{Y_i}{L_i} \right) + hp \left(1 - \frac{L_{it}}{N_{it}} \right) \left(\frac{Y_i}{L_i} \right) \right] \left(\frac{1+g}{1+r} \right)^{t-j} \quad (6.73)$$

Where:

PV_{ij} : present discounted value of lost market and non-market output for a person of age j in state i who dies in a certain year

g : growth rate of GDP per worker

$\Pi_{ij,t}$ is the probability that a person of age j in state i survives to age t

r : discount rate

In CPAT, $W_{ij,t} = W_p$ (does not change by age or within countries). We will also consider only deaths up to 64, neglecting work force above 65. These assumptions, together with assuming $hp = 0$, allow us to rewrite Equation 6.73 as Equation 6.74.

$$PV_j = W * \sum_{t=j}^{64} \pi_{j,t} * \left(\frac{1+g}{1+r} \right)^{t-j} \quad (6.74)$$

Rewriting Equation 6.74, we obtain:

$$PV_j/W = \sum_{t=j}^{64} \pi_{j,t} * \left(\frac{1+g}{1+r} \right)^{t-j} \quad (6.75)$$

The total output lost due to air pollution attributed mortality is obtained using Equation 6.76.

$$TotalOutputLost = \sum_j PV_{ij} D_{ij} \quad (6.76)$$

With D_{ij} the number of deaths attributed to air pollution in state i of age j .

GDP loss due to air pollution morbidity

In CPAT, we estimate the years lived with disability due to pollution (see Section 6.6.3.2). We value those years, in which people in working age are not able to work, or the output loss associated with morbidity using Equation 6.77.

$$M_{ij} = W_{ij} * YLD_{ij} \quad (6.77)$$

Table 6.15 presents the data sources used for the different productivity parameters needed to quantify output losses.

Table 6.15: Parameters for productivity

Parameter		Data sources
α	Labor's share of GDP	Guerriero (2019), includes 117 countries. If there isn't data available for a country, we use the world's average labor share of GDP, of 65%.

Parameter		Data sources
Y_i	GDP	World Bank national accounts data, and OECD National Accounts data files
$\frac{L_{it}}{N_{it}}$	Labour to population	Employment to population ratio, 15+, total (%) (modeled ILO estimate), International Labour Organization, ILOSTAT database. Data retrieved in April 2019
L_{it}	Number of persons that are employed	$L = LaborForcetotal * (1 - unemployment)$ Labor force ³⁰ derived using data from International Labour Organization, ILOSTAT database and World Bank population estimates. Labor data retrieved in April 2019. Unemployment from International Labour Organization, ILOSTAT database. Data retrieved in April 2019.
hp	Household production	Not included in CPAT

³⁰Labor force comprises people ages 15 and older who supply labor to produce goods and services during a specified period. It includes people who are currently employed and people who are unemployed but seeking work as well as first-time jobseekers. Not everyone who works is included, however. Unpaid workers, family workers, and students are often omitted, and some countries do not count members of the armed forces. Labor force size tends to vary during the year as seasonal workers enter and leave.

Parameter		Data sources
$\Pi_{it,t}$	Probability of survival	The probability of survival is the probability that an individual would have survived to each future year of his working life. The probability of death ³¹ is obtained from Global Burden of Disease Collaborative Network (2018) for every country and age group. The probability of survival up to 64 years is calculated as follows: $\pi_j = \prod_j^{64} (1 - \text{Prob of death}_j)$
g	growth rate of GDP per worker	ILO indicators ³² , up to 2023: - SDG indicator 8.2.1 - Annual growth rate of output per worker (GDP constant 2010 USD) (%). After 2023, we assume a growth rate equal to the rate in 2023.

³¹The probability that a person dies during an interval of two ages (e.g., between birth and age 5), if the rates of all-cause mortality in a specified year of interest would remain constant into the future.

³²Data available in https://www.ilo.org/ilostat-files/Documents/Bulk_ilostat_en.html#, accessed in December 2019

Parameter		Data sources
r	Discount rate	CPAT allows the user to select among 3 options: i) Use the real interest rate for the country, ii) Using a 3% discount rate, as recommended in Robinson, Hammitt, and O’Keeffe (2019), iii) Input manually a discount rate. In case the user selects the first option, r will be the real interest rate ³³ (%) from the International Monetary Fund, International Financial Statistics and data files using World Bank data on the GDP deflator ³⁴ . That data covers 127 countries. Data is available up to 2018. After 2018, it’s assumed an interest rate equal to the average of the rates between 2014 and 2018.

6.7.3.1 CPAT operationalization

From the GBD Results Tool, we obtained deaths probabilities for five-years buckets. For instance, we know the probability of dying between 25 to 29 years old ($d_{25,29}$). The probability $d_{25,29}$ is equal to the sum of the probability of dying at 25, at 26, at 27, at 28 and at 29 years old, as shown in Equation 6.78.

$$d_{25,29} = d_{25} + d_{26} + d_{27} + d_{28} + d_{29} \quad (6.78)$$

For simplicity and to keep the file size at a reasonable level, we will assume that the probability of dying at every age contained in each bucket is the same, and equal to the bucket dying probability divided by 5, as presented in Equation 6.79.

³³Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator. The terms and conditions attached to lending rates differ by country, however, limiting their comparability.

³⁴Data available in <https://data.worldbank.org/indicator/FR.INR.RINR>, accessed in December 2019.

$$d_{25} = d_{26} = d_{27} = d_{28} = d_{29} = \frac{d_{25,29}}{5} \quad (6.79)$$

The survival probability for each age inside each age-bucket is presented in Equation 6.80.

$$\pi_{25,29} = \left(1 - \frac{d_{25,29}}{5}\right) = \pi_{25} = \pi_{26} = \pi_{27} = \pi_{28} = \pi_{29} \quad (6.80)$$

To implement Equation 6.75, let's do $\left(\frac{1+g}{1+r}\right) = a$. Then, Equation 6.75 operationalized for 5 years bucket in CPAT is presented in Equation 6.81.

$$\frac{PV_{25-29}}{W} = \pi_{25,29} * \sum_{k=0}^2 a^k + \pi_{25,34} * \sum_{k=3}^7 a^k + \dots + \pi_{25,64} * \sum_{k=43}^{47} a^k \quad (6.81)$$

Where $k = t - j$

To solve the sums inside Equation 6.81, we can apply the following formula:

$$\sum_{k=0}^n a^k = \frac{1 - a^{n+1}}{1 - a} \quad (6.82)$$

Equation 6.82 can be used to solve the sum terms that start in $k \neq 0$, as shown in Equation 6.83.

$$\sum_{k=m}^n a^k = \sum_{k=0}^n a^k - \sum_{k=0}^m a^k = \frac{1 - a^{n+1}}{1 - a} - \frac{1 - a^{m+1}}{1 - a} \quad (6.83)$$

6.7.4 Health expenditure

In CPAT, we use total expected health expenditure from 2017 to 2050 from the IHME (Global Burden of Disease Health Financing Collaborator Network (2019a)).

We follow Preker et al. (2016) to estimate the share of total health expenditure than can be attributed to pollution. The assumption is a constant expenditure per DALY (Disability adjusted life years).

In CPAT, we calculate the share of the total burden of disease that's attributed to the 6 main causes related to pollution, using data from the GBD Results Tool (Institute for Health Metrics and Evaluation (IHME) (2020)). The share of the burden of disease for disease d , country c and year t , $\%BoD_{d,c,t}$, is calculated according to Equation 6.84.

$$\%BoD_{d,c,t} = \frac{DALYs_{d,c,t}}{\text{TotalDALYs}_{c,t}} \quad (6.84)$$

The total health expenditure attributed to pollution HEAP can be calculated using Equation 6.85.

$$HEAP_{c,t} = \sum_d \%BoD_{d,c,t} * PAF_{d,t} * THE_{c,t} \quad (6.85)$$

Where:

$PAF_{d,t}$: population attributable fraction for disease d in year t

$THE_{c,t}$: Total health expenditure for country t in year t

$DALYs_{d,c,t}$: Disability adjusted life years, for disease d , country c and year t

In CPAT, we distribute health expenditure between government, prepaid private, out-of-pocket and development assistance for health using IHME estimations for 2019 (Global Burden of Disease Health Financing Collaborator Network (2019a)).

6.7.5 Value of the statistical life

In CPAT, we value averted mortality using the value of the statistical life or VSL. It's important to notice that the VSL does not represent the value of individual lives. Rather, the VSL is a measure of the rate at which individuals are willing to exchange money to reduce small risks of death within a certain period of time. This concept is used in benefit-cost analyses, and we include it in CPAT to assign a monetary value to averted mortality due to a carbon price policy.

The VSL can be transferred following the methodology from OECD (2012) and Narain and Sall (2016), according to Equation 6.86.

$$VSL_c = VSL_{OECD,2005} * \left(\frac{Y_c}{Y_{OECD,2005}} \right)^b * (1 + \%P + \%Y)^b \quad (6.86)$$

Where:

c : Country to which VSL is being transferred to.

$VSL_{OECD,2005}$: Median VSL in OECD countries in 2005, in 2005 \$USD PPP

Y : GDP per capita in PPP

b : Income elasticity for VSL in country c

% Y : Income growth after 2005

% P : inflation according to consumer price index

In CPAT, we first transform OECD VSL from 2005 USD PPP to 2011 PPP, using Equation 6.87.

$$VSL_{OECD, t, 2011PPP} = VSL_{OECD, 2005} * \left(\frac{Y_{OECD, t}}{Y_{OECD, 2005}} \right)^{0.8} * (1 + \% P_{2005, 2011})^{0.8} \quad (6.87)$$

Secondly, we transfer the OECD VSL from 2014 (in 2011 USD PPP) to the destiny country, according to Equation 6.88.

$$VSL_{OECD, 2014} = VSL_{OECD, 2014} * \left(\frac{Y_{c, 2014}}{Y_{OECD, 2014}} \right)^b \quad (6.88)$$

Thirdly, we project VSL in time using projected GDP per capita for country c , according to Equation 6.89.

$$VSL_{c, t} = VSL_{c, 2014} * \left(\frac{Y_{c, t}}{Y_{c, 2014}} \right)^b \quad (6.89)$$

Finally, we convert the VSL from 2011 dollars to dollars in the “Results Year” (equal to 2019), using the 2019 price deflator for the country of destiny.

In CPAT, income elasticity is assumed equal to 0.8 for high-income countries and 1.2 for middle and low-income countries. The user can also input manually a different elasticity and a different VSL value in the Advanced tab of CPAT.

Table 6.16 and Table 6.17 present the values assumed to transfer the VSL from OECD countries.

Table 6.16: Assumptions and data sources for VSL transfer

Variable	Assumption	Source
$VSL_{OECD, 2005}$	3 million USD in 2005, in 2005 PPP dollars	OECD (2012), Table 6.1
b	0.8 for high income countries and 1.2 for middle and low-income countries	Narain and Sall (2016)

Table 6.17: Consumer price index and GDP per capita, OECD countries

Year	CPI OECD	GDP per head of population OECD (2011 \$US PPP)
2005	82.0	35,407.8
2006	84.1	36,248.1
2007	86.2	36,921.0
2008	89.4	36,738.5
2009	89.9	35,198.6
2010	91.5	36,011.9
2011	94.1	36,554.1
2012	96.2	36,813.9
2013	97.7	37,130.2
2014	99.4	37,696.5
2015	100.0	38,413.8
2016	101.1	38,859.1
2017	103.4	39,589.2

Source: OECD (2021a) and OECD (2021b)

6.7.6 Time Structure of averted deaths

When quantifying and valuing premature mortality, it is often assumed that there is a “cessation lag,” or time distribution of averted mortality after a reduction in exposure (US EPA (2013)). The time structure we selected assumes that 30% of mortality reductions occur during the first year, 50% occurs over years 2 to 5 and 20% over years 6 to 20, after the PM2.5 reduction takes place.

When valuing averted mortality using the value of statistical life (VSL), it is possible to calculate the present value of the benefit from reduced premature deaths by applying the discount rate to the number of deaths themselves and then multiplying by the VSL. In CPAT, the user can select the discount rate among 3 options: i) a discount rate of 3%, consistent with the recommendation in Robinson et al. (2019); ii) a discount rate that represent the interest rate paid by the country’s government and iii) a manual input of discount rate. When using a 3% discount rate, the present value of premature deaths reduced is 0.906 times the number of undiscounted premature averted deaths. When using a higher discount rate, for example a rate of 8%, the factor is reduced to 0.798 (see Table 6.18).

Table 6.18: Time distribution of averted premature deaths

		3% discount rate	8% discount rate		
	Deaths distribution in time	Time discount factor	Fraction deaths*time discount factor	Time discount factor	Fraction deaths*time discount factor
Year 0	30.0%	1.00	0.300	1.00	0.300
Year 1	12.5%	0.97	0.121	0.93	0.116
Year 2	12.5%	0.94	0.118	0.86	0.107
Year 3	12.5%	0.92	0.114	0.79	0.099
Year 4	12.5%	0.89	0.111	0.74	0.092
Year 5	1.3%	0.86	0.012	0.68	0.009
Year 6	1.3%	0.84	0.011	0.63	0.008
Year 7	1.3%	0.81	0.011	0.58	0.008
Year 8	1.3%	0.79	0.011	0.54	0.007
Year 9	1.3%	0.77	0.010	0.50	0.007
Year 10	1.3%	0.74	0.010	0.46	0.006
Year 11	1.3%	0.72	0.010	0.43	0.006
Year 12	1.3%	0.70	0.009	0.40	0.005
Year 13	1.3%	0.68	0.009	0.37	0.005
Year 14	1.3%	0.66	0.009	0.34	0.005
Year 15	1.3%	0.64	0.009	0.32	0.004
Year 16	1.3%	0.62	0.008	0.29	0.004
Year 17	1.3%	0.61	0.008	0.27	0.004
Year 18	1.3%	0.59	0.008	0.25	0.003
Year 19	1.3%	0.57	0.008	0.23	0.003
Total	0.906		0.798		
Lag factor					

Source: Own elaboration Note: $\text{Time discount factor} = 1/(1+r)^{(t-t_0)}$

6.7.7 Travel time saved

Excess travel time is one of the consequences of road congestion. In CPAT, we estimate excess travel time, increased road damage, increased injuries, and additional vehicle operating costs attributable to congestion. The methodology used is described in the document Road Transport documentation. Here we only describe the methodology used to quantify changes in travel time, in time units, with respect to free a flow condition.

We estimate travel time per vehicle-kilometer in free flow and in congested conditions for 416 cities in 57 countries, using TomTom data (see Equation 6.91 and Equation 6.90). The time domain used is “All Days Full Day”.

Congestion travel time per vehicle-kilometer, $CongestionTT$, is calculated using Equation 6.90.

$$CongestionTT_{2019}[\text{min/vehkm}] = \frac{AccumulatedTravelTime_{2019}[\text{min}]}{TotalVehKM_{2019}[\text{vehkm}]} \quad (6.90)$$

TotalVehicleKM corresponds to the multiplication of the number of vehicles and the average distance traveled and is reported in the TomTom database.

The travel time per vehicle-kilometer under free flow conditions is calculated using Equation 6.91.

$$FreeFlowTT\left[\frac{\text{min}}{\text{vehkm}}\right] = \frac{CongestionTT_{2019}\left[\frac{\text{min}}{\text{vehkm}}\right]}{\left(1 + \frac{CI_{2019}}{100}\right)} \quad (6.91)$$

Where CI is the average congestion index in 2019.

We estimate vehicle-kilometers traveled per capita using total vehicle-kilometers from the World Road Statistics data (International Road Federation (2018a)) and countries total population (World Bank (2019b)). For those countries not included in the WRS database, we assume the average vehicle-kilometers traveled per capita between the regional mean and the income level mean.

Using vehicle-kilometers traveled per capita, together with the congestion index CI and the free flow travel time, we can estimate total travel time each year t , in time units, using Equation 6.92.

$$Travel\ time_t = \left(1 + \frac{CI_t}{100}\right) * FreeFlowTT\left[\frac{\text{min}}{\text{vehkm}}\right] * VehKm\ per\ capita\ \left[\frac{\text{vehkm}}{\text{year}}\right] * UrbanPopulation_{15+,t} \quad (6.92)$$

In CPAT, there are estimations for the congestion index for each year, under the baseline scenario and a carbon price scenario. Using the Equation 6.92, we can quantify travel time for each year under each scenario. Time savings attributed to a carbon price are equal travel time in the baseline minus travel time in the carbon price scenario.

We value those time savings following Robinson et al. (2019). We value travel time at a rate of 50% the after-tax wage rate. We use gross earnings³⁵ data from ILO and then we apply a

³⁵Glossary of terms here: <https://dev-ilstat.pantheonsite.io/resources/concepts-and-definitions/description-earnings-and-labour-cost/>

factor to estimate after-tax wages. The factor used for OECD countries is the “average income tax rate as % of gross wage earnings”. For other countries, we use the average factor from OECD countries, equal to 16%. When we value travel time savings, we do so by considering only the population above 15 years old, since younger population does not participate in the labor market.

Some implied assumptions: We assume that free flow travel time and vehicle-kilometers traveled per capita are constant in time. Vehicle-kilometers traveled are the same across the population, regardless of age or other considerations. Tomtom’s data is representative of vehicles not using their devices.

6.7.8 Value of morbidity using years lived with disabilities (YLDs)

Another approach to value morbidity in CPAT is based on a method proposed in Bank (2022). Under this method, we convert YLDs to ‘annual disease days’ M and we value them using a fraction of a country’s daily wage.

First, annual disease days are calculated from YLDs, for each country as:

$$M = \sum_{c=1}^n YLD_c * \frac{365}{DW_c} \quad (6.93)$$

Where:

YLD_c : years lost to disease c

DW_c : Average disability weight of disease c attributed to PM2.5

The cost of a day lived with a disease c , c_c , is calculated a fraction of the daily wage w (in each country), as presented in Equation 6.94. The term D corresponds is set at 0.4, and is associated to the disability weight of a severe condition, with severely restricted work and leisure activity and a substantial medical cost.

$$c_c = w * \frac{DW_c}{D} \quad (6.94)$$

The average daily wage, w , was calculated using the methodology explained in Section 6.7.3.

Finally, the cost of morbidity is calculated as the multiplication of annual disease days and the cost of each day lived with disease.

$$Cost\ of\ Morbidity = \sum_{i=1}^n c_c * M \quad (6.95)$$

Using this method to value morbidity attributed to air pollution, we calculate the share of morbidity costs as a share of mortality costs.

6.7.9 Air pollution externalities per unit of fuel

The health impacts attributed to air pollution are calculated jointly for ambient and household pollution (see Section 6.6.3), following the methodology from Global Burden of Disease Health Financing Collaborator Network (2020). Although the health impacts are estimated jointly, we compute an average externally cost per unit of fossil fuel burnt, which affects only ambient pollution.

After the health impacts have already been quantified, the air pollution externality computation is made as follows:

1. We compute the average ambient air pollution attributed mortality per $\mu\text{g}/\text{m}^3$ of PM2.5 as total mortality attributed to ambient PM2.5 in a certain year (referred to as “attributable burden” in previous chapters) divided by the total ambient PM2.5 that year.
2. Using the emission factor (for each fuel and sector, for each country) and the emissions-to-concentrations model selected, we compute the ambient PM2.5 contributed by one unit of fuel used (in $\mu\text{g}/\text{m}^3$ of PM2.5 per ktoe).
3. We multiply the average ambient air pollution attributed mortality per $\mu\text{g}/\text{m}^3$ (step 1) with the ambient PM2.5 contributed by one unit of fuel used (step 2), obtaining the number of attributed deaths by unit of fuel used (deaths/ktoe).
4. We multiply the metric calculated in step 3 with the VSL for the corresponding year and country, obtaining the externality value in dollars per ktoe. We add to this number morbidity costs (for ambient air pollution), according to the methodology described in Section 6.7.8.
5. We convert energy units to express the externality in a commonly used metric for each fuel, considering the relevant calorific values in each country and fuels densities when needed. For instance, for gasoline, the externality is expressed as US\$ per liter, while, for coal, the externality is expressed as US\$ per GJ.

6.8 Validation: comparison with other models

6.8.1 Health impacts of pollution

In the following figures, we compare CPAT results with external models. Green dots represent CPAT results, and the blue line represents the results from the external model. When the

green dots are above the blue line (45 degrees line), CPAT estimates are higher, and when the green dots are below the line, CPAT estimates are lower.

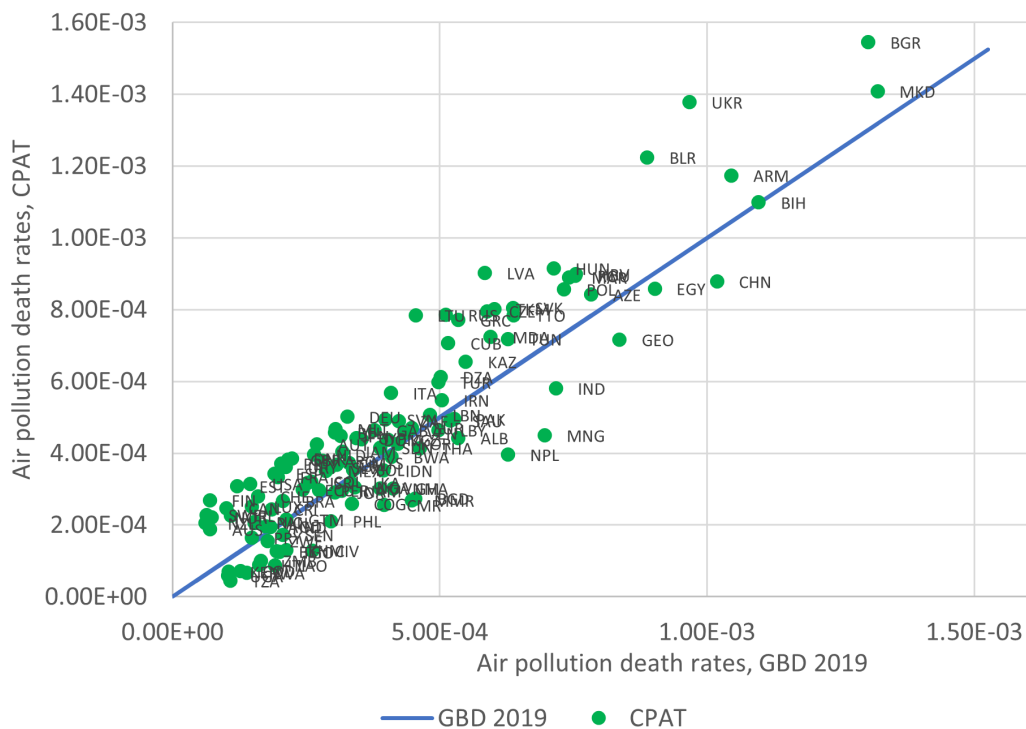


Figure 6.28: CPAT estimation of ambient PM_{2.5} air pollution death rates versus GBD2019 estimates

Source: CPAT results and Global Burden of Disease Health Financing Collaborator Network (2020)

6.8.2 Emissions

Source: CPAT results, European Environment Agency (2020) and ECLIPSE V5a Global Emission Fields - Global Emissions (2015)

Source: CPAT results, European Environment Agency (2020) and ECLIPSE V5a Global Emission Fields - Global Emissions (2015)

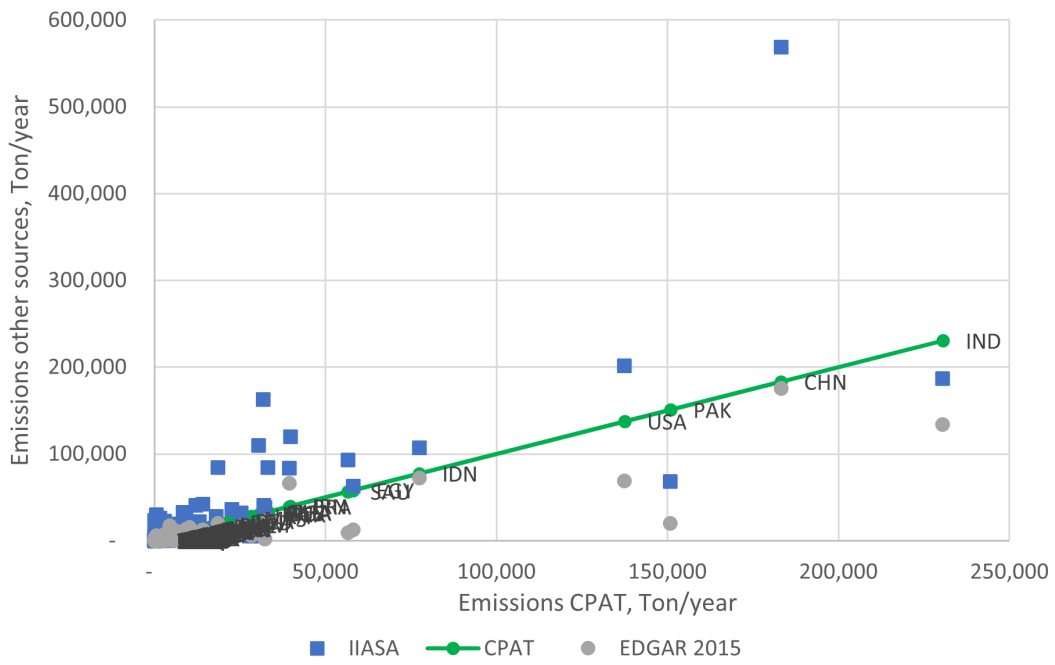


Figure 6.29: PM2.5 emissions in the transport sector, CPAT 2020 versus EDGAR 2015 and IIASA 2020

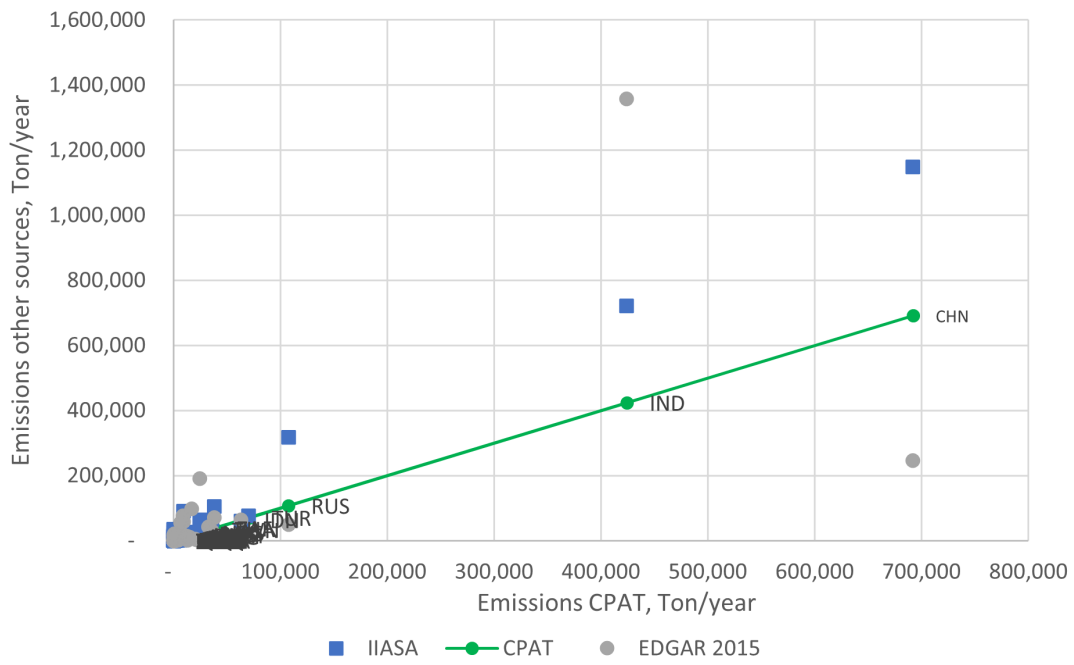


Figure 6.30: PM2.5 emissions in the power sector, CPAT 2020 versus EDGAR 2015 and IIASA 2020

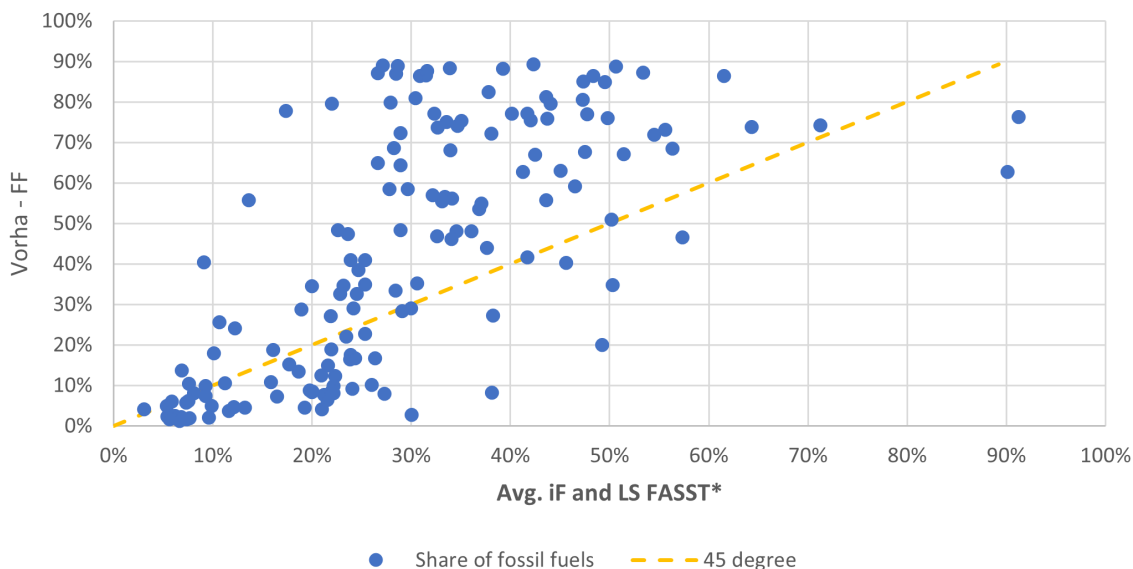


Figure 6.31: Comparison of the share of fossil fuels contribution to ambient PM_{2.5} from Vohra et al. (2021) and CPAT “Avg. iF and LS FASST” (Option 6 of this documentation)

6.8.3 Concentrations: share of fossil fuels on ambient PM_{2.5}

Source: Own elaboration. Note: Vohra et al. (2021) share of FF contribution to ambient PM_{2.5} if higher than in CPAT for 61% of countries

Source: Own elaboration. Note: Vohra et al. (2021) share of FF contribution to ambient PM_{2.5} if higher than in CPAT for 55% of countries

Source: Own elaboration. Note: Vohra et al. (2021) share of FF contribution to ambient PM_{2.5} if higher than in CPAT for 44% of countries

6.8.4 Externalities from pollution

6.9 Caveats

The health impacts are calculated using global relative risk functions and global data bases regarding exposure to pollution, baseline incidence and others. Global databases are constructed using country level databases, but in many cases, they are adjusted and standardized. This may lead to differences among the data used in CPAT and local databases. If differences among CPAT and local data is an issue, an advanced Excel user could modify any inputs

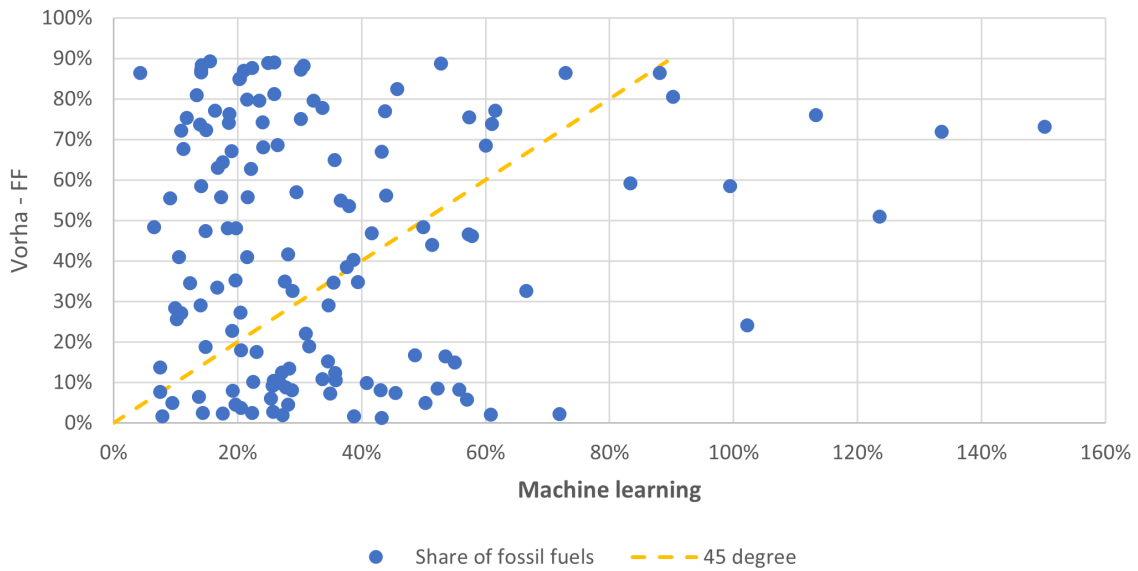


Figure 6.32: Comparison of the share of fossil fuels contribution to ambient PM2.5 from Vohra et al. (2021) and CPAT “**Machine Learning**” (Option 5 in this documentation)

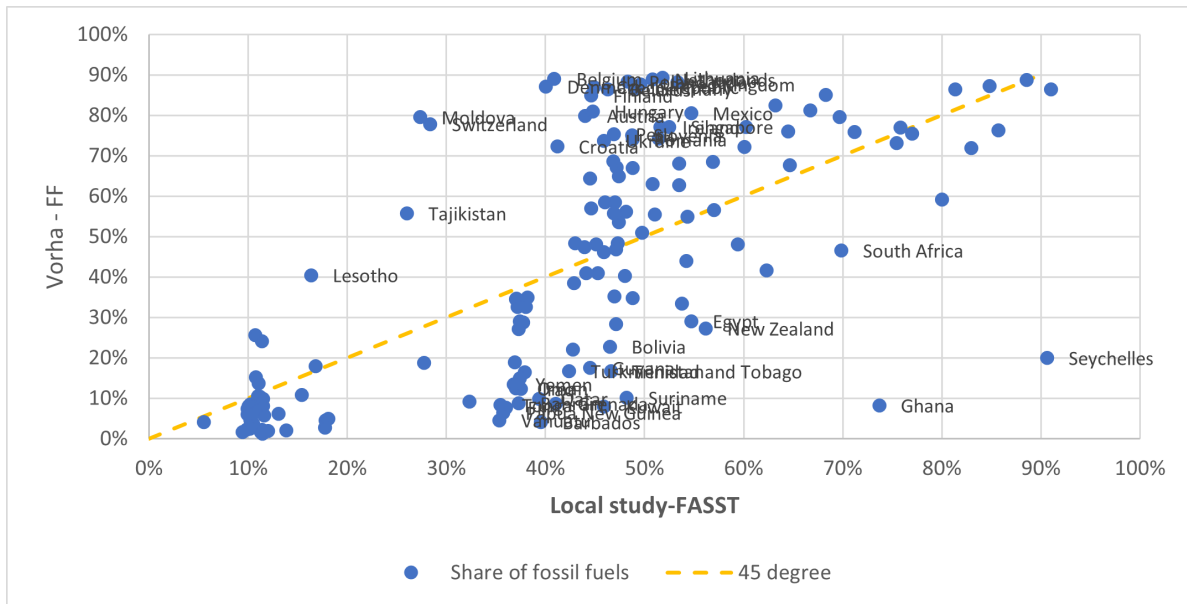


Figure 6.33: Comparison of the share of fossil fuels contribution to ambient PM2.5 from Vohra et al. (2021) and CPAT “**Local Study-FASST**” (Option 2 in this documentation)

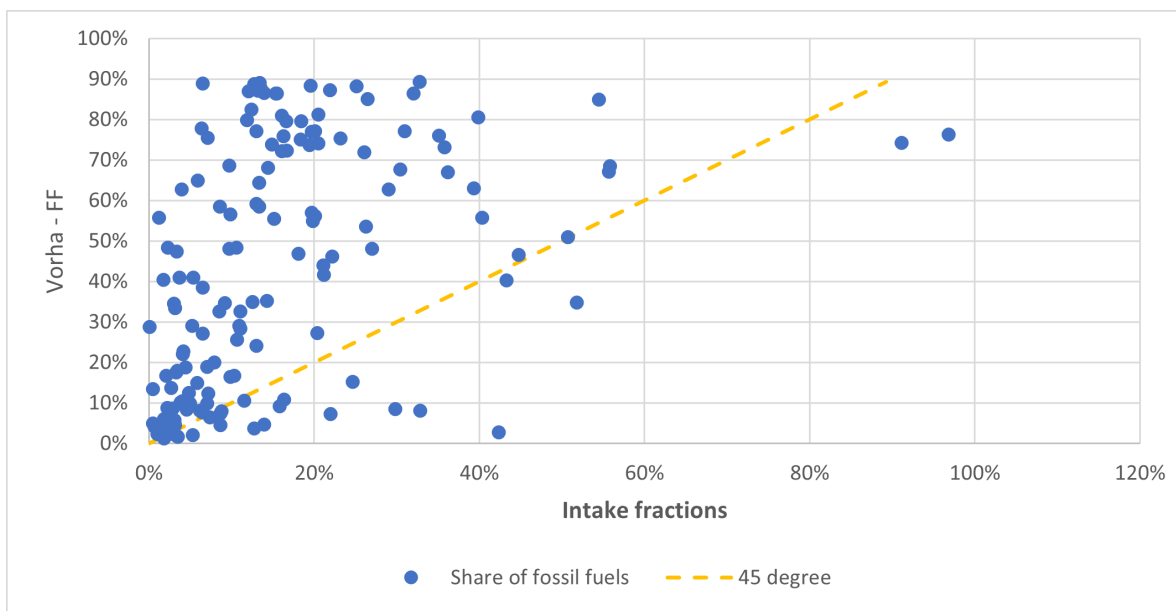


Figure 6.34: Comparison of the share of fossil fuels contribution to ambient PM2.5 from Vohra et al. (2021) and CPAT “**Intake fractions**” (Option 4 in this documentation)

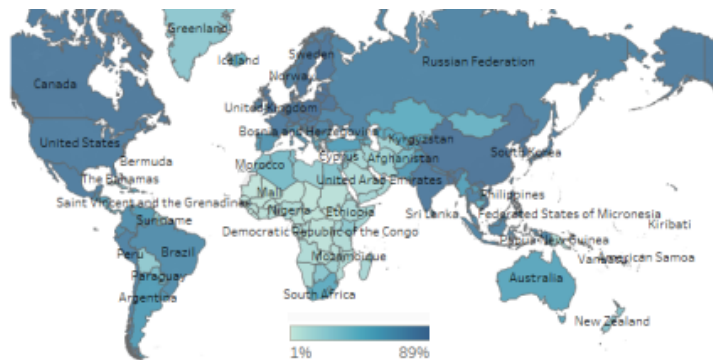
in CPAT, since the spreadsheet is open, but this would require a deep understanding of the tool.

Another issue to be aware of is the national and yearly scope of CPAT. This can be a limitation of CPAT analysis because the dynamics of air pollution can vary widely inside countries and throughout the year. CPAT intends to represent population weighted average air pollution for average pollution during a calendar year.

Another caveat is the uncertainty on the calculation of emissions, the relationship between emissions and ambient concentration, the health impacts and the economic values used to monetize the impacts of pollution. CPAT at the time is providing a central estimate for all calculations, without indicating uncertainty on estimations. This caveat could be partially addressed by using the “MT tool” (described in the user guide) to do a sensitivity analysis on the assumptions used.

It is important to consider that, even though CPAT performs well when compared to other more complex models, this does not guarantee that CPAT results will always be consistent with other more advance models. We have compared baseline estimates with external global sources, to make sure that we represent the baseline properly. Many checks have been performed in the Mitigation module too, which results drive the air pollution results. These checks do not guarantee that the policy impacts obtained using CPAT will be similar to those obtained from other more complex models. Further checks will need to be performed in a policy/country-specific context. CPAT allows the user to change assumptions and inputs, such that the tool

Contribution using GEOS-Chem
(Vohra et al. 2019)



Average contribution using
CPAT

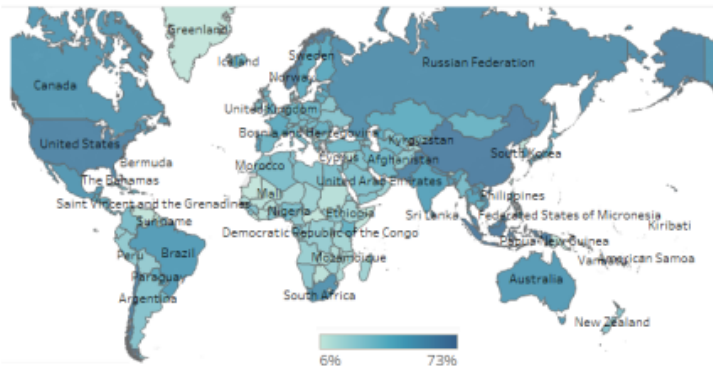


Figure 6.35: Modeled contribution of fossil fuels to ambient PM_{2.5}. Vohra et al. (2021) versus CPAT (average among 6 options to relate emissions and concentrations)

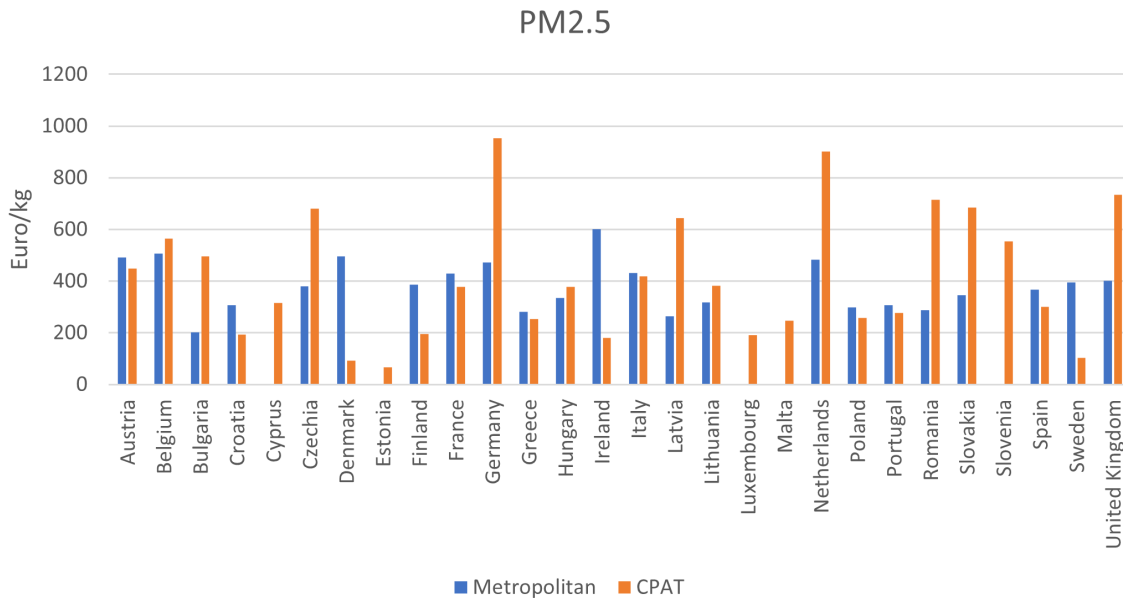


Figure 6.36: Comparison among CPAT results and Korteland (2022)

can be adjusted properly when needed.

Overall, the results from the air pollution in CPAT are conservative in the sense the results are likely underestimating the health impacts of a climate policy. This is the case in big part because the default configuration of the air pollution variables yields conservative contribution from fossil fuels to air pollution. The user can change the predefined options and calibrate the tool to make the results consistent with other sources of information available.

6.10 Appendices

6.10.1 CPAT codes, Air Pollution tab.

Air pollution tab codes:

Variable	Code	Description
Series	paf	Population attributable fraction
	rr	Relative risk
	em	Emission
	con	Concentration
	pop	Population

Variable	Code	Description
	ph	Proportion of population using solid fuels for cooking and thus exposed to household pollution
	inc	Incidence proportion
	dth	Deaths
	Yll	Years of life lost
	Yld	Years lived with disabilities
	daly	Disability-adjusted life years
	mrf	Multiple risk factor (for COPD)
	src	Source-receptor coefficients from FASST
Pollutants	pm2.5	PM2.5 (concentration)
	O3	Ozone (concentration)
Risks	Oap	Ambient or outdoors pollution
	Hap	Household air pollution
	Hop	Ambient + household pollution
	bur	Ambient pollution, using Burnett et al 2018
Diseases	lri	Lower respiratory diseases
	Lun	Tracheal and lung cancer
	Cop	Chronic obstructive pulmonary disease
	Dme	Diabetes mellitus type II
	Str	Stroke
	Ihd	Ischemic heart disease
	dep	Depressive disorders
	dne	Diseases for neonates: Sudden infant death syndrome, Diarrheal diseases, Lower respiratory infections, Upper respiratory infections, Otitis media, Meningitis, Neonatal disorders, Encephalitis
Age	All	
	25 to 64	
	65+	
Area	Urb	Urban areas
	rur	Rural areas
	all	Urban and rural areas
Others	Conc.	Concentration by sector according to user's information, with precursors weight calculated using FASST
	pm2.5.usr	Concentration by sector according to local study, with precursors weight calculated using FASST
	conc.pm2.5.lst	Concentration by sector according to local study, with precursors weight calculated using CM (from Apte or Fantke)
	Conc.pm2.5.lst	Concentration by sector according to local study, with precursors weight calculated using CM (from Apte or Fantke)
	eln	Elastic net model to relate emissions and concentrations

6.10.2 Relative Risk IER GBD 2019

Table 6.20: IER GBD 2019 for lung cancer, COPD, diabetes mellitus type II, LRI, low birth-weight and pre-term birth

$PM_{2.5}$ ($\mu\text{g}/\text{m}^3$)	Tracheal, bronchus, and lung cancer	Chronic obstructive pulmonary disease	Diabetes mellitus type 2	Lower respiratory infections	Low birth- weight	preterm birth
600	1.76	5.19	1.56	2.48	1.3281	1.6024
500	1.73	4.54	1.54	2.44	1.2870	1.5498
400	1.70	3.89	1.52	2.40	1.2459	1.4973
300	1.67	3.24	1.50	2.34	1.2049	1.4448
200	1.64	2.59	1.48	2.07	1.1638	1.3922
150	1.62	2.27	1.47	1.88	1.1432	1.3659
120	1.61	2.05	1.46	1.74	1.1309	1.3502
90	1.57	1.83	1.46	1.59	1.1186	1.3336
75	1.54	1.71	1.45	1.51	1.1124	1.3120
60	1.49	1.58	1.45	1.42	1.1062	1.2722
45	1.42	1.45	1.44	1.33	1.1001	1.2201
30	1.32	1.31	1.40	1.22	1.0922	1.1603
25	1.28	1.26	1.37	1.19	1.0875	1.1388
20	1.24	1.21	1.33	1.15	1.0809	1.1161
15	1.19	1.16	1.28	1.12	1.0721	1.0916
10	1.13	1.11	1.21	1.08	1.0603	1.0645
5	1.07	1.06	1.11	1.04	1.0404	1.0342
0	1.00	1.00	1.00	1.00	1.0000	1.0000

Source: Own elaboration based on Global Burden of Disease Health Financing Collaborator Network (2020)

Table 6.21: IER GBD 2019 for Ischemic heart disease and stroke

$PM_{2.5}$ ($\mu\text{g}/\text{m}^3$)	25- 29	30- 34	35- 39	40- 44	45- 49	50- 54	55- 59	60- 64	65- 69	70- 74	75- 79	80- 84	85- 89	90- 94	95+	
Ischemic heart dis- ease	600	2.83	2.69	2.53	2.41	2.29	2.14	2.06	1.93	1.83	1.76	1.64	1.53	1.47	1.36	1.27
	500	2.79	2.65	2.49	2.37	2.25	2.11	2.02	1.89	1.79	1.72	1.61	1.50	1.44	1.34	1.25
	400	2.75	2.61	2.45	2.33	2.20	2.07	1.98	1.86	1.76	1.68	1.57	1.48	1.41	1.32	1.24

	PM2.5- ($\mu\text{g}/\text{m}^3$)	25- 34	30- 39	35- 44	40- 49	45- 54	50- 59	55- 64	60- 69	65- 74	70- 79	75- 84	80- 89	85- 94	90- 95+	
	300	2.71	2.57	2.41	2.29	2.16	2.03	1.93	1.82	1.72	1.64	1.54	1.45	1.38	1.29	1.22
	200	2.67	2.52	2.37	2.24	2.12	1.99	1.89	1.78	1.68	1.60	1.50	1.42	1.35	1.27	1.20
	150	2.65	2.50	2.35	2.22	2.10	1.97	1.87	1.76	1.66	1.58	1.49	1.40	1.33	1.26	1.19
	120	2.64	2.49	2.34	2.21	2.08	1.96	1.86	1.75	1.65	1.57	1.48	1.40	1.32	1.25	1.18
	90	2.61	2.47	2.31	2.19	2.06	1.94	1.84	1.73	1.64	1.55	1.46	1.38	1.31	1.24	1.18
	75	2.53	2.39	2.24	2.13	2.01	1.90	1.80	1.69	1.61	1.52	1.44	1.37	1.30	1.23	1.17
	60	2.37	2.24	2.12	2.01	1.91	1.81	1.73	1.63	1.55	1.48	1.41	1.34	1.27	1.21	1.16
	45	2.16	2.05	1.95	1.86	1.78	1.70	1.62	1.54	1.48	1.41	1.35	1.29	1.24	1.19	1.14
	30	1.88	1.80	1.72	1.66	1.60	1.54	1.48	1.42	1.37	1.32	1.28	1.23	1.19	1.15	1.11
	25	1.76	1.69	1.63	1.58	1.52	1.47	1.42	1.36	1.33	1.28	1.24	1.20	1.17	1.13	1.10
	20	1.64	1.58	1.53	1.49	1.44	1.40	1.36	1.31	1.27	1.24	1.20	1.17	1.14	1.11	1.08
	15	1.50	1.46	1.42	1.38	1.35	1.32	1.28	1.24	1.22	1.19	1.16	1.14	1.11	1.09	1.07
	10	1.35	1.32	1.29	1.27	1.24	1.22	1.20	1.17	1.15	1.13	1.11	1.10	1.08	1.06	1.05
	5	1.18	1.17	1.15	1.14	1.13	1.12	1.11	1.09	1.08	1.07	1.06	1.05	1.04	1.03	1.02
	0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Stroke	600	3.53	3.31	3.08	2.88	2.73	2.52	2.37	2.21	2.09	1.94	1.82	1.73	1.63	1.54	1.43
	500	3.49	3.27	3.04	2.84	2.69	2.48	2.33	2.17	2.05	1.90	1.78	1.69	1.59	1.49	1.39
	400	3.44	3.23	3.00	2.80	2.65	2.44	2.29	2.13	2.01	1.87	1.74	1.65	1.55	1.45	1.35
	300	3.40	3.19	2.96	2.76	2.61	2.41	2.25	2.09	1.97	1.83	1.71	1.61	1.50	1.41	1.31
	200	3.36	3.15	2.92	2.72	2.56	2.37	2.21	2.06	1.93	1.79	1.67	1.57	1.46	1.37	1.27
	150	3.33	3.13	2.90	2.70	2.54	2.35	2.19	2.04	1.91	1.78	1.65	1.54	1.44	1.34	1.25
	120	3.32	3.12	2.89	2.68	2.53	2.33	2.18	2.03	1.90	1.76	1.64	1.53	1.43	1.33	1.24
	90	3.28	3.08	2.85	2.66	2.50	2.31	2.16	2.01	1.88	1.75	1.63	1.52	1.41	1.32	1.23
	75	3.13	2.93	2.72	2.55	2.39	2.21	2.08	1.94	1.83	1.71	1.59	1.50	1.40	1.31	1.22
	60	2.84	2.67	2.49	2.34	2.21	2.06	1.95	1.83	1.73	1.62	1.53	1.44	1.36	1.28	1.20
	45	2.47	2.33	2.20	2.07	1.97	1.85	1.77	1.67	1.59	1.51	1.43	1.36	1.30	1.23	1.17
	30	2.03	1.94	1.85	1.76	1.69	1.61	1.55	1.48	1.43	1.37	1.31	1.27	1.22	1.17	1.12
	25	1.88	1.80	1.72	1.65	1.59	1.52	1.47	1.41	1.37	1.32	1.27	1.23	1.19	1.14	1.11
	20	1.72	1.65	1.59	1.53	1.48	1.43	1.39	1.34	1.30	1.26	1.22	1.19	1.15	1.12	1.09
	15	1.55	1.50	1.45	1.41	1.37	1.33	1.30	1.26	1.24	1.20	1.17	1.15	1.12	1.09	1.07
	10	1.38	1.34	1.31	1.28	1.26	1.23	1.20	1.18	1.16	1.14	1.12	1.10	1.08	1.06	1.05
	5	1.19	1.18	1.16	1.14	1.13	1.12	1.11	1.09	1.08	1.07	1.06	1.05	1.04	1.03	1.02
	0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Source: Own elaboration based on Global Burden of Disease Health Financing Collaborator Network (2020)

In CPAT, we use the RR values from Table 6.20 and Table 6.21. Since the tables do not include every possible value for PM2.5, we interpolate interpolating between the closest higher and lower values, using Equation 6.96.

$$RR_{\text{actual}} = RR_{\text{high}} - \frac{RR_{\text{high}} - RR_{\text{low}}}{PM_{\text{high}} - PM_{\text{low}}} * (PM_{\text{high}} - PM_{\text{actual}}) \quad (6.96)$$

6.10.3 Quantification of health effects in CPAT

The RR associated with exposure to household (and ambient) pollution in the baseline, RR_{HAP}^0 , can be expressed as the baseline mortality rate for those exposed to HAP (and OAP), λ_{HAP}^0 , divided by the mortality rate that would be observed in the absence of pollution, λ_{TMREL} . This relationship is presented in Equation 6.97.

$$RR_{\text{HAP}}^0 = \frac{\lambda_{\text{HAP}}^0}{\lambda_{\text{TMREL}}} \quad (6.97)$$

In the same way, the RR associated with exposure to ambient pollution in the baseline, RR_{OAP}^0 , can be expressed as the baseline mortality rate for those exposed to OAP, λ_{OAP}^0 , divided by the mortality rate that would be observed in the absence of pollution, λ_{TMREL} . This relationship is presented in Equation 6.98.

$$RR_{\text{OAP}}^0 = \frac{\lambda_{\text{OAP}}^0}{\lambda_{\text{TMREL}}} \quad (6.98)$$

Baseline mortality M_0 is observable and can be expressed as presented in Equation 6.99.

$$M_0 = \text{Population} * p_H * \lambda_{\text{HAP}}^0 + \text{Population} * (1 - p_H) * \lambda_{\text{OAP}}^0 \quad (6.99)$$

Using Equation 6.97 and Equation 6.98, we can rewrite baseline mortality in Equation 6.99 as Equation 6.100.

$$M_0 = \text{Population} * p_H * RR_{\text{HAP}}^0 * \lambda_{\text{TMREL}} + \text{Population} * (1 - p_H) * RR_{\text{OAP}}^0 * \lambda_{\text{TMREL}} \quad (6.100)$$

Using Equation 6.100, we can solve for λ_{TMREL} . The result for λ_{TMREL} , the mortality rate in the absence of PM2.5 pollution risk, is presented in Equation 6.101.

$$\lambda_{\text{TMREL}} = \frac{M_0}{\text{Population}} * \left(\frac{1}{p_H * RR_{\text{HAP}}^0 + (1 - p_H) * RR_{\text{OAP}}^0} \right) \quad (6.101)$$

For each age group and condition, there is a λ_{TMREL} , defined in Equation 6.101. The total changes in mortality are presented in Equation 6.102:

$$M = M_0 * \left\{ 1 - \left(\frac{p_H^1 * RR_{HAP}^1 + (1 - p_H^1) * RR_{OAP}^1}{p_H^0 * RR_{HAP}^0 + (1 - p_H^0) * RR_{OAP}^0} \right) \right\} \quad (6.102)$$

Where $M = M_0 - M_1$

λ_{TMREL} : Mortality incidence proportion if pollution was at the TMREL level

M_0 : Baseline mortality

M_1 : Mortality under policy scenario

p_H^0 : Proportion of households using solid fuels for cooking in the baseline scenario

p_H^1 : Proportion of households using solid fuels for cooking in the carbon price scenario

RR_{HAP}^1 : RR associated with exposure to ambient and household pollution in the carbon price scenario.

RR_{OAP}^0 : RR associated to ambient pollution in the baseline scenario

RR_{OAP}^1 : RR associated to ambient pollution in the carbon price scenario

In summary, the deaths are calculated as follows:

	Baseline air pollution deaths	Policy air pollution deaths
Exposed to HAP and OAP	$(RR_{HAP}^0 - 1) * \text{pop} * p_H^0 * \lambda_{TMREL}$	$(RR_{HAP}^1 - 1) * \text{pop} * p_H^1 * \lambda_{TMREL}$
Exposed to OAP	$(RR_{OAP}^0 - 1) * \text{pop} * (1 - p_H^0) * \lambda_{TMREL}$	$(RR_{OAP}^1 - 1) * \text{pop} * (1 - p_H^1) * \lambda_{TMREL}$

6.10.4 Some unit conversions

- Emission factors. The “original” unit from GAINS EF is *kton/PJ*. Since energy balances in CPAT are expressed in *ktoe*, we apply a unit conversion for emission factors, from *kton/PJ* to *ton/ktoe*

$$EF \left[\frac{\text{ton}}{\text{ktoe}} \right] = EF \left[\frac{\text{kton}}{\text{PJ}} \right] * \frac{1 \text{ PJ}}{10^6 \text{ GJ}} * \frac{10^3 \text{ ton}}{1 \text{ kton}} * \frac{41868 \text{ GJ}}{1 \text{ ktoe}} \quad (6.103)$$

- From *ktoe* to volume of *m3*:

$$1 \text{ ktoe} = 1 \text{ ktoe} * \frac{1 \text{ Kcal}}{1 * 10^{-10} \text{ ktoe}} * \frac{1}{\text{CalVal} \left[\frac{\text{kcal}}{\text{kg}} \right]} * \frac{1}{\text{Dens} \left[\frac{\text{ton}}{\text{m}^3} \right]} * \frac{1 \text{ ton}}{10^3 \text{ kg}} \quad (6.104)$$

- To convert from ktoe to m3, multiply ktoe by the following factor:

$$\text{Conv_ktoe_to_liter} = \frac{1}{\text{CalVal} \left[\frac{\text{kcal}}{\text{kg}} \right]} * \text{Dens} \left[\frac{\text{ton}}{\text{m}^3} \right]} * 10^7 \quad (6.105)$$

- To convert from ktoe to liters, multiply ktoe by the following factor:

$$\text{Conv_ktoe_to_liter} = \frac{1}{\text{CalVal} \left[\frac{\text{kcal}}{\text{kg}} \right]} * \text{Dens} \left[\frac{\text{ton}}{\text{m}^3} \right]} * 10^{10} \quad (6.106)$$

- 1 kcal= 1e-10 ktoe
- To convert from kton/PJ (emission factors unit) to ton/liter, when calorific value is in PJ/ton:

$$\frac{1 \text{ kton}}{\text{PJ}} * \frac{1000 \text{ ton}}{1 \text{ kton}} * \text{CalVal} \left[\frac{\text{PJ}}{\text{ton}} \right]} * \text{dens} \left[\frac{\text{ton}}{\text{m}^3} \right]} * \frac{1 \text{ m}^3}{1000 \text{ L}} \quad (6.107)$$

- To convert from kton/PJ (emission factors unit) to ton/liter, when calorific value is in Kcal/kg:

$$\frac{1 \text{ kton}}{\text{PJ}} * \frac{1000 \text{ ton}}{1 \text{ kton}} * \text{CalVal} \left[\frac{\text{Kcal}}{\text{kg}} \right]} * 1000 \frac{\text{kg}}{\text{ton}} * \text{dens} \left[\frac{\text{ton}}{\text{m}^3} \right]} * \frac{1 \text{ m}^3}{1000 \text{ L}} * \frac{1 \text{ PJ}}{2.39 * 10^{11} \text{ Kcal}} \quad (6.108)$$

- To convert from ktoe to liter:

$$1 \text{ ktoe} * \frac{1}{\text{CalVal} \left[\frac{\text{Kcal}}{\text{kg}} \right]} * \frac{1 \text{ Kcal}}{1 * 10^{-10} \text{ ktoe}} * \frac{1}{\text{dens} \left[\frac{\text{ton}}{\text{m}^3} \right]} * 1000 \frac{\text{kg}}{\text{ton}} * \frac{1 \text{ m}^3}{1000 \text{ liter}} \quad (6.109)$$

Note: Calorific values and densities are from IEA (2019).

6.10.5 Comments from 2021 review and summary of changes

Below are the comments from the original review in 2021, and then our further comments in 2022. The comments in the table do not include those where reviewers were already in agreement with CPAT. Most comments and answers are a summary of the original version.

Comment

Response 2021

Response 2022

Incidence rate vs. incidence proportion

The methodology document provided the definitions for key technical terms, including that for the incidence rate, which forms part of the overall method used in calculating the burden of disease. However, the definition presented in the document seems to be referring to the incidence proportion and not the rate. In epidemiological terms, there is a distinction between the two measures

Thanks for the precisions made on the definitions for incidence proportion and rate. We did use the correct measures, following the GBD study. We will correct the documentation.

The comment was incorporated into CPAT documentation.

Age-group considerations for lower respiratory tract infections (LRTI)

The methodology currently considers all age groups combined for LRTI estimates and relies on the same Integrated Exposure Response (IER) function across the board for this outcome. Exposure to household air pollution almost doubles the risk for childhood pneumonia and is responsible for 45 percent of all pneumonia deaths in children less than 5 years of age. Household air pollution is also a risk for pneumonia in adults, and contributes to nearly 28 percent of all adult pneumonia-related deaths. Given implications from the application of carbon pricing, especially in relation to leakage to biomass, and households opting to use solid fuels for cooking and heating as a result, mortality estimates among those in the under 5 years old age-group is likely to increase. Therefore, stratifying LRTI cause-specific mortality by age-group to capture this specific age-group would be of extremely high relevance – even more so from an operational perspective.

We fully agree that a disaggregated analysis by age group, in buckets of five years would be the best approach, and even more disaggregated to include neonatal effects. Unfortunately, in CPAT we are working with more aggregated age groups: Under 15, 15 to 24, 25 to 64, above 65, and neonatal. We did this aggregation due to limited file size in the tool. Because of this, we cannot differentiate the effects among children under 5, but hopefully we will use a more disaggregated analysis in the CPAT version outside Excel.

As before, more detailed disaggregation is not feasible in the Excel version of the tool. But the aggregates estimate of CPAT replicate well the results obtained with more disaggregated data.

In countries with high household pollution, after a carbon price we generally obtain a net reduction in health effects, despite increase household health effects.

Considering methodology applied in the Household Air Pollution Intervention Tool (HAPIT) to estimate health benefits

The team provided a comparison between HAPIT and CPAT, concluding that CPAT is based on more recent methodologies, but HAPIT does a better job differentiating exposure among women, children and men. This element could be added in a future CPAT version, developed outside Excel.

As before, regarding household pollution (not the focus of CPAT), no additional disaggregation is possible, to consider different exposure patterns among women, children and men. Regrettably we are already at the limit of Excel capabilities.

The CPAT dashboard is user-friendly and is easy to navigate. It is unclear, however, where and how to update certain parameters should the need arise (e.g. changes in IER functions, or in VSL estimates) or to allow for country-specific inputs. To this end, a more detailed user manual would be extremely valuable to have.

We hope that a few months of testing (with the team involved in each study) would give us a good idea of whether the tool can be roll out to other teams (and what type of training and support may be needed).

Now we have produced a user's guide, that intends to guide the user about policies configuration and parameters settings. This guide corresponds to Chapter 1 of CPAT documentation.

(Emissions – concentrations – health outcomes:

Of course, and the team is keenly aware of this, CPAT has to rely on simplified ways of modelling the complex relationships (such as for example using intake fractions instead of using chemical transportation modelling of relating emissions to concentrations), but for a policy tool, this in my view is certainly more than good enough. That said, I wonder if in the future we can experiment with going beyond intake fractions

Besides intake fractions, we have included other options to relate emissions and concentrations: i) TM5-FASST model, ii) Source apportionment information, in combination with TM5-FASST results and iii) Elastic Net and OLS model. We are also in the process of implementing in CPAT the results of a machine learning modeling to related emissions and concentrations, by emitting source type.

In addition to the models indicated during the previous review, we have added the following models to relate emissions to concentration: i) a machine learning methodology (simplified) and ii) Average of intake fractions and source apportionment in combination with TM5-FASST.

We have also expanded the source apportionment studies available in CPAT.

I appreciate the effort made to show how CPAT's figures correspond to IIASA's, EDGAR's and GBD's, and think those are useful symmetries to show. That said, I do want to point out that this does not imply that the impact of a certain EFR on air pollution and health outcome would deliver the same results whether it's impact is modelled with CPAT or the more complex models.

We have compared the air pollution module baseline estimates with external global sources, to make sure that we represent the baseline within the results from other more complex models. You are right that these checks do not guarantee that the policy impacts modeled in CPAT will be similar to the policy impacts obtained from other more complex models. Further checks will need to be performed in a policy/country-specific context and we have made sure that the tool allows the user to change assumptions and inputs, such the tool can be adjusted properly when needed.

We added a section of "caveats" to the documentation that includes this point.

I am currently looking at the relationships between air pollution and infant mortality, globally, as part of an ASA activity. We will be producing a concentration-response curve for this relationship, which you may choose to include into CPAT as an alternative to the GBD function.

Sure, we can add this new concentration-response curve for infant mortality in CPAT.

The paper is currently in the process of being published and the focus was on the impact of PM2.5 on increased pregnancy stunting (rather than infant mortality). This outcome can negatively affect children even after they recover from stunting.

At this stage, we cannot include this effect in CPAT, but we already have children and neonatal health effects in the tool.

The pollution model includes plenty of interesting information. The direct economic link is via the reduction in labor supply and deaths related to pollution. However, there are in effect two mechanisms at play - which could be added. The first is associated with the extensive margin - i.e. the number of employed individuals not going to work due to illness. The second is related to the intensive margin - the reduction in the number of productive hours worked. This is important in a country context where affected laborers tend to be low-skilled and where laborers can be drawn from an unemployed pool and put to work immediately (the case where employing the services of an unemployed worker to replace the affected worker is costless). If this is the case, then the direct pollution effect on labor could be negligible.

However, if all workers are exposed to pollution, then what matters is the intensive margin - i.e. the work effort. Reducing pollution will have an extra benefit to society - increased labor effort and more efficient means of production regardless of the substitutability of labor.

At the moment the CPAT tool describes the economic benefit or reducing pollution in terms of disability adjusted life years. This is an extensive margin concept where labor rotation

rates are not accounted for (i.e. the probability of drawing an unskilled worker from the unemployment pool to replace the sick worker). Accounting for these rotation rates complicates the modeling but adds another element of realism. The economic cost will no longer be associated with DALY's multiplied by income, but with DALY's adjusted for labor replacement effects, multiplied by incomes.

Thanks for your comments and suggestions. We agree that the “intensive margin” effect can be more relevant, due to a generalized drop in labor effort when workers are exposed to pollution. There is evidence that, besides working days lost and DALYs (both included in CPAT), productivity may decrease among workers that do attend to work. The drop in productivity has been studied in different working settings and locations of the world (see table below). We have not yet incorporated the results from the different studies into CPAT. The results of the last paper in the table (Fu, Viard, and Zhang 2017) could be implemented, if we believe that country specific results could be extrapolated and used in other countries.

Moreover, there is growing evidence on cognitive effects of air pollution in adults (Allen et al. 2017; Zhang, Chen, and Zhang 2018) and neurodevelopment issues children (WHO 2018), affecting human capital formation. This implies that air pollution has both short term and long-term effects in productivity, but so far, we have not been able to incorporate them in CPAT.

As before, although the literature on productivity effects of pollution is growing, we still face the issue of location and setting specific studies, that cannot confidently be extrapolated to a global setting, for broad sectors of the economy.

When cooking fuels are exempt, the spill-over effects on consumption of various fuels particularly biomass, and the resulting health (and other development) effects should be accounted for if possible.

Thanks for this comment. Exactly, we allow the user to exempt, or rather rebate, cooking fuels in order to alleviate concerns of spill-over effects into increased biomass use. For the proportion of the consumption for which no exemption is chosen, at present we model explicit substitution into biofuels with carbon pricing (not modelled when these fuels are exempt). So, we are able to see the modelled differences in health effects between carbon price and non-carbon price (with and without exemptions).

This point was clarified during the previous review

Below is a list of the changes made in CPAT, between the 2021 review (in March) and August 2022.

Type	Description
Development	Additional summary metrics of externalities (per unit of fuel burned), for additional fuels and sectors
	Additional indicators of externalities related to years of life lost (YLL), years lived with disabilities (YLD)

Type	Description
	<p>Additional indicators of externalities differentiating for population in working age</p> <p>Inclusion of the marginal impact on global temperature, compared to emissions level of the baseline year</p> <p>New source apportionment studies were added</p> <p>New average method to relate emissions to concentrations: average of intake fractions and local-study/TM5-FASST</p> <p>New metrics about the total damage of pollution as share of GDP, using VSL and forgone output</p> <p>New option to adjust baseline year results (2019) to GBD 2019 study</p> <p>Additional VSL options</p> <p>Implementation of the results from machine learning method, for PM2.5 and ozone to relate emissions to concentrations in the different sectors.</p> <p>For household pollution, we added a projected HAP level and exposure, based in historical trends</p> <p>The relative risk functions were extended to up to 2000 ug/m3</p>
Other changes	<p>Emissions of local pollutants were moved to the mitigation module</p> <p>New emission factors for CO2, other GHGs and local pollutants</p> <p>Changes in graphs with results</p> <p>Dashboard results now include in their title a link to the results in the air pollution tab</p> <p>Change to a different baseline year</p> <p>Many modifications to run CPAT using the Multi Scenario tool</p> <p>Definition of default options to configure the air pollution tab</p> <p>Corrections in case modeled concentrations are above observed ones (issue arising from emissions to concentration models being calibrated with different data bases)</p> <p>Changes to more efficient (faster) formulas</p> <p>Standardization of codes (for diseases, risks, etc.)</p>
Fixes	<p>Many small fixes in formulas</p> <p>Runs to check errors that arises for particular countries</p> <p>Corrections to the calculation of GWP100, affected by corrections in emission for biofuels and methane.</p> <p>Correction of the average emission factors option, to calculate emissions for local air pollution health effects</p> <p>Correction of the externality of LPG. It had problems for certain emissions to concentration models.</p>

7 Road Transport Module

7.1 Summary

Carbon taxes impact fuel prices and thereby shape driving behavior. In particular, carbon taxes increase incentives to substitute away from private vehicles towards more fuel-efficient means of transport. As road traffic has many externalities aside carbon emissions, carbon taxes may lead to a reduction in road transport-related externalities such as congestion, accidents and road damage. To estimate the magnitude of these co-benefits, the CPAT Road Transport Module quantifies the effect of a user-defined carbon tax or road fuel tax on (a) the intensity of congestion as measured by the time lost relative to free-flowing traffic, (b) the number of road fatalities, and (c) the maintenance cost due to road damage.

The Road Transport Module is based on elasticities that we estimate using an international country-year level dataset. This dataset is compiled from many sources and describes road transport, as well as general demographics and economic variables. The dataset covers the time from 1994 to 2021 and 186 countries, so that we can use within-country and between-country variation for identification. We estimate elasticities with respect to fuel prices and with respect to fuel taxes, as well as short and long-run elasticities. We estimate country-specific elasticities based on global coefficients and country-specific covariates.

The magnitude of the resulting elasticities are broadly in line with the literature: for a 10% fuel price increase from a carbon tax, total vehicle-km traveled decrease in the short run on average by 2.8 %; congestion levels decrease by 3.4 %; accident fatalities decrease by 6.1 %; and road damage decreases by 4.4 % in the long run.

The estimated elasticities are used within CPAT to produce policy forecasts of total vehicle-km traveled, congestion levels, accident fatalities and road damage cost. By choosing a country and inputting different parameters for a policy in the dashboard, the user obtains a series of graphs showing the time series with and without the policy, as well as the policy impact defined by the difference of the two time series.

Important caveats of the CPAT Road Transport Module include the assumed linearity of effects, which may potentially not apply to large policy changes. Moreover, econometrically estimated elasticities take the historic capital stock as given and do not predict the impact of disruptive technological changes such as electric vehicles (EVs). Finally, CPAT does not measure the externality cost of non-realized trips.

7.2 List of acronyms

CCKP Climate Change Knowledge Portal (from the World Bank)

FAD IMF's Fiscal Affairs Department

GHO Global Health Observatory (from the World Health Organization)

GIZ Gesellschaft für Internationale Zusammenarbeit (German development agency)

IEA International Energy Agency

IMF International Monetary Fund

NCEI National Centers for Environmental Information (United States)

OECD Organisation for Economic Co-operation and Development

OLS Ordinary Least Squares (econometric estimation method)

SDG Sustainable Development Goals

SDR Sustainable Development Report (Sachs et al. (2019))

UNECE United Nations Economic Commission for Europe

VKT Vehicle-kilometers traveled (analogous to the US American vehicle-miles traveled)

WDI World Development Indicators (from the World Bank)

WGI World Governance Indicators (from the World Bank)

WHO World Health Organization

WRS World Road Statistics (from the International Road Federation)

wrt “with respect to”

7.3 Introduction

Aside carbon emissions, road transport causes various externalities. The most important transport externalities examined here are congestion, road damage and accidents. These externalities are not the explicit target of carbon taxes, but also decline when the total distance traveled declines. Such reductions in externalities occur as a “side effect” to the direct goal of a carbon tax and are commonly called *co-benefits* (Parry et al. (2014)).

As a tool for assessing the overall impact of carbon tax reforms across the globe, CPAT predicts the magnitude of these co-benefits, among others for the transport sector. The methodology relies on econometric estimations of long-run and short-run elasticities of externalities with

respect to fuel prices. The fuel price change induced by a carbon tax is then multiplied by the elasticities to predict the transport co-benefits of the carbon tax policy.

The following sections will first give an overview over the relevant literature; then present the data sources used and explain the methodology for estimating the elasticities of externalities with respect to fuel prices. In a next section, we will present the estimation results on three transport externalities: congestion, road damage and accidents. Finally, we present the Excel implementation of this work in CPAT.

7.3.1 Vehicle-kilometers traveled (VKT)

We do not consider VKT (analogous to the US American vehicle-miles traveled, VMT) a policy target *per se* but include it in order to illustrate one of the main channels through which fuel prices affect congestion, road damage and accidents. Reductions in VKT may be a result of people transitioning to less transport-intensive activities, other transport modes, in particular public/collective transport options, closer workplaces and residence location choice (Molloy and Shan (2013)).

In particular, a carbon tax may incite passengers to travel together, such that a reduction of vehicle-km may be achieved *without* a reduction in passenger-trips, by increasing the rate of passengers per vehicle. Bento, Hughes, and Kaffine (2013) show that the average number of users increases with fuel prices, because users carpool (i.e. share a vehicle) more. Carbon taxes may also deter detours, so that vehicle-km, and even passenger-km, may be reduced without a reduction in passenger-trips (see Figure 7.1).

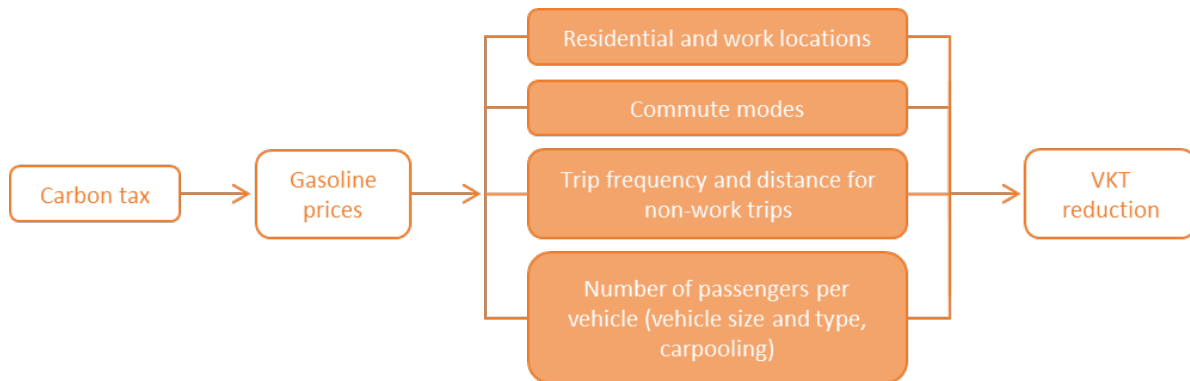


Figure 7.1: Schematic representation of the link between carbon tax and VKT

Note: Channels (in orange boxes) are shown to illustrate the economic theory; they are not modeled/estimated separately within CPAT.

The negative relationship between fuel prices and VKT is well established in the economics literature. The literature provides a large number of empirical estimates of the elasticity of VKT wrt fuel prices. Table 7.1 lists a selection of these estimates: most commonly, the

estimates of VKT elasticity range from -0.05 to -0.50. A review paper found the mean estimate to be -0.10 in the short run and -0.29 in the long run (Goodwin, Dargay, and Hanly (2004)).

Some of these responses take time, so the long-run gasoline price elasticity of road deaths is likely to exceed the short-run elasticity. However, high fuel prices also push consumers to invest into more fuel-efficient vehicles, either buying cars that are more efficient or switching from cars to motorcycles (or other modes). In this case, the literature has extensively discussed the importance of the *rebound effect*, defined as efficiency induced consumption or, more plainly, the idea “buy a more fuel-efficient car, drive more” (Gillingham, Rapson, and Wagner (2016)). The rebound effect might cause long-run VKT elasticity to be *lower* than short-run VKT elasticity.

Table 7.1: Literature estimates of the elasticity of VKT wrt fuel prices

Study	Country	Fuel price elasticity of road		Note
		Short run	Long run	
US				
Small and Van Dender (2007)	US	-0.05	-	VKT elasticity.
Burger and Kaffine (2009)	US	-0.16	0.22	VKT elasticity during peak congestion hours in Los Angeles.
Bento, Hughes, and Kaffine (2013)	US	-0.05		Roads without carpool lanes in Los Angeles. Elasticity is for number of trips.
Gillingham (2014)	US	-0.22		Vehicle-level data for California. Effect allows >1 years of response, but is not long-run. VKT elasticity.
Gillingham, Jenn, and Azevedo (2015)	US	-0.10		Vehicle-level data for Pennsylvania. VKT elasticity.

Study	Country	Fuel price elasticity of road	Note
Haughton and Sarkar (1996)	US	-.16 to -.07	- .58 to -.21 VKT elasticity at US state level.
Huang and Burris (2015)	US	-0.06	Mean for a sample of toll roads. Elasticity is for number of trips.
Other countries			
RAYMOND (2003)	Spain	0.34	- 0.53 Elasticity is for number of vehicle trips on toll roads.
Crôtte, Noland, and Graham (2009)	Mexico	0.12	VKT elasticity.
Khoo, Ong, and Khoo (2012)	Malaysia	0.16	Uses road sensor data for 2008.
Frondel, Ritter, and Vance (2012)	Germany	0.58	VKT elasticity.
Delsaut (2014)	France	0.14	- 0.28 VKT elasticity.
Kwon and Lee (2014)	South Korea	0.11	Elasticity is for number of vehicle trips.
Odeck and Johansen (2016)	Norway	0.11	- 0.24 VKT elasticity.

Notes: Studies are chronologically ordered. Listed papers are a sample of prior studies. “Short run” and “long run” do not have the same definitions in all studies. Adapted from Burke, Batsuuri, and Yudhistira (2017) and Moshiri (2020).

7.3.2 Congestion

Congestion is the result of interaction between the limited vehicle capacity of a given facility and the demands for space by individual users. The costs of congestion occur in the form of excess travel time, increased expected damage and injury from accidents among vehicles, and additional vehicle operating costs for wear and fuel (Murphy and Delucchi (1997)).

The relationship of total VKT to congestion is straightforward (see Figure 7.2): the less vehicles on the road, the smaller the congestion problem (Sugiyama et al. (2008)). This theoretical relationship has been documented in the literature for decades (Johnson (1964)). When people share vehicles (carpooling) or substitute to public transport, the reduction in congestion may be achieved with constant total passenger-km (Bento, Hughes, and Kaffine (2013)).

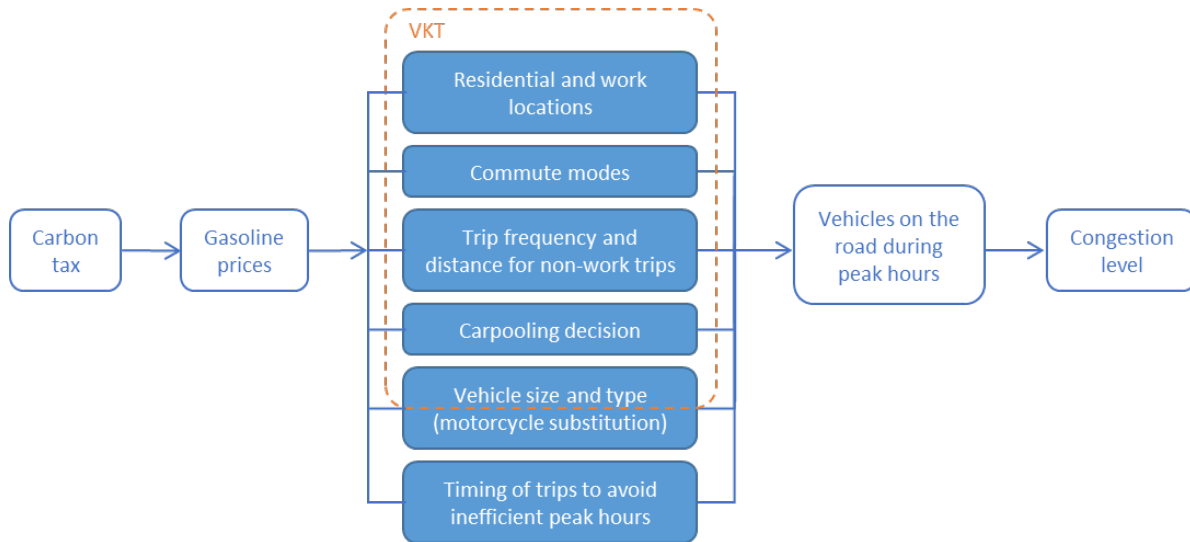


Figure 7.2: Schematic representation of the link between carbon tax and congestion

Notes: Channels (in blue boxes) are shown to illustrate the economic theory; they are not modeled/estimated separately within CPAT.

Empirically, congestion has been difficult to measure until very recently. Conventional measurement methods are costly, such as employing humans to count, establishing cameras or installing wires on the road. The resulting measurements only cover a limited number of precise locations and often only short periods of time. More recently, the development of mobile communication technology has allowed newer measures such as the congestion indicators of Waze, Google Maps, Inrix and TomTom. These GPS-based data cover larger areas over long periods of time and are highly disaggregated.

Given the limited/recent availability of congestion data, the empirical literature on the impact of fuel prices on congestion levels is relatively scarce. Burger and Kaffine (2009) find that a USD 1 increase in fuel prices reduces congestion and raises average freeway speeds by approximately 7% during rush-hour periods. They estimate short-run elasticity with a methodology similar to ours and find estimates ranging from -0.12 to -0.29. In an older study, Dahl (1979) finds an estimate of -0.35 for the elasticity of speed wrt fuel price. Cohen and Roth (2017) find that higher diesel prices lead to less but heavier trucks on the road, thereby reducing congestion.

Burke, Batsuuri, and Yudhistira (2017) examine the reaction to a fuel tax reform in Indonesia and find a fuel price elasticity of motor vehicle flows (number of vehicles on toll roads) between

-0.1 and -0.2. They estimate that Indonesia's fuel subsidy reforms of 2013 and 2014 have reduced traffic pressure by around 10%, relative to the counterfactual without reform.

The externality cost of congestion can be measured in monetary equivalent by multiplying time lost in traffic congestion by the value of travel time (Abrantes and Wardman (2011)).

7.3.3 Road accident fatalities

Road traffic injury is now the leading cause of death for children and young adults aged 5-29 years. It is the eighth leading cause of death for all age groups surpassing HIV/AIDS, tuberculosis and diarrheal diseases (World Health Organization (2018b)).

Road accidents are a function of factors including road user behavior, road characteristics, vehicle characteristics, and the distances driven (vehicle-kilometers traveled, VKT) on roads by different types of drivers. Research has also shown that economic variables affect road accident risk exposure. Among these, fuel prices and key macroeconomic measures such as the unemployment rate have been the focus of prior studies rates (Ahangari et al. (2014); Gerdtham and Ruhm (2006); International Transport Forum (2015)). The negative effect of fuel prices on the risk of fatal accidents is well established in the literature.

For international comparisons, the literature considers data on fatalities more reliable than data on the number of accidents and number of injuries (Luoma and Sivak (2007); Sauerzapf, Jones, and Haynes (2010); World Health Organization and others (2013)). This is why most studies concentrate on deadly crashes, when trying to assess the relationship of fuel prices and road accidents. Chi et al. (2010) is a notable exception to this rule.

The relationship from fuel prices (and thus taxes) to accidents is multifactorial (see Figure 7.3), as shown in Chi, Porter, et al. (2013). Several aspects may be summarized to a principal channel which is VKT. Reduced driving decreases the exposure of both vehicle occupants and others to road crashes.

Note: Channels (in red boxes) are shown to illustrate the economic theory; they are not modeled/estimated separately within CPAT.

In addition to reducing VKT, higher gasoline prices might also lead to a reduction in road deaths per kilometer driven. One reason is that, to conserve fuel, drivers might reduce high-speed driving and so-called "aggressive driving" (high rates of acceleration and braking). Another reason is that high-risk drivers, including the young, the old, and those taking leisure-related trips, are particularly sensitive to gasoline prices (Morrissey and Grabowski (2011); Sivak (2009)). Higher gasoline prices also result in substitution from heavier to lighter, more fuel-efficient cars, which are associated with a lower overall number of road deaths per kilometer traveled (Gayer (2004); White (2004)). Substitution to bus travel may also reduce overall road safety risks.

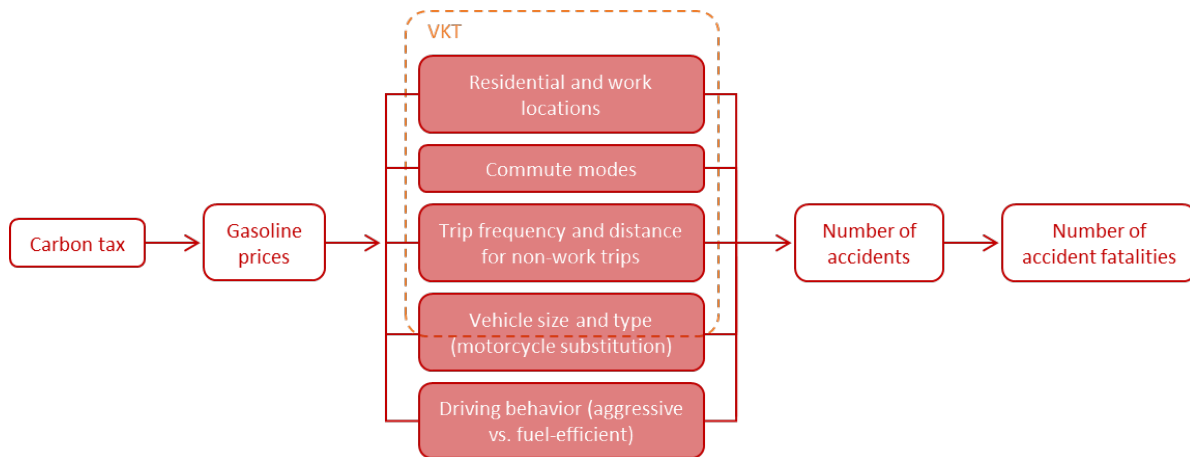


Figure 7.3: Schematic representation of the link between carbon tax and accidents, adapted from Chi, Porter, et al. (2013)

However, through other channels higher gasoline prices might actually lead to *more* rather than fewer road deaths. Higher gasoline prices reduce congestion and thereby increase average speed (Burger and Kaffine (2009)), which increases the risk of fatal crashes. Fuel price-induced substitution to motorcycles, which are more fuel-efficient, may also cause additional road deaths (Hyatt et al. (2009); Wilson, Stimpson, and Hilsenrath (2009)). In particular, substitution to lighter cars and motorcycles would explain why long-run elasticities of accidents wrt fuel prices would be *smaller* in absolute magnitude than short-run elasticities.

Many studies in this field concentrate on the United States. Some authors argue that the effect of higher gasoline prices on road deaths operates via a reduction in VKT (Grabowski and Morrisey (2004)), whereas others report also a reduction in road deaths per VKT (Chi et al. (2010); Chi, Quddus, et al. (2013); Grabowski and Morrisey (2006); Haughton and Sarkar (1996); Montour (2011); Sivak (2009)). Sivak (2009) explains this reduction by the disproportionate reduction in leisure driving (riskier than commuter driving) and rural driving (more risky than urban driving).

Leigh and Wilkinson (1991) examine the relationship between gas price, gas tax, and road fatalities for all 50 states using a multiple regression framework. They find that a 1% increase in gas tax leads to a 0.18% to 0.20% reduction in road fatalities, but that gas prices are not statistically significant in explaining road fatalities. They use a different method, using cent-per-gallon rather than a log-log specification as does this study. A later study by Grabowski and Morrisey (2004), using 1983 to 2000 state-level data and a panel model to investigate the relationship between gas prices and road fatalities, finds that a 1% increase in gasoline prices reduces road fatalities by 0.23%. Looking only at Mississippi, Chi et al. (2010) finds a short-run elasticity of -0.25 and a long-run elasticity of -0.47. For Minnesota, Chi, Quddus, et al. (2013) find an elasticity of -0.219 for fatal crashes wrt to fuel prices and their estimates are higher in rural areas than in urban areas.

In an international study, Burke and Nishitateno (2015) find a 1% increase in the gasoline pump price would reduce road fatalities by 0.3% to 0.6%. Around 35,000 road deaths per year could be avoided by the removal of global fuel subsidies. Litman (2012) presents a scatterplot for 16 Organization for Economic Co-operation and Development (OECD) countries that shows a negative association between average gasoline prices and traffic fatality rates. Using a panel model of 16 industrialized countries, Ahangari et al. (2014) find an elasticity of -0.22 after controlling for VKT.

Other country-specific short-term elasticity estimates include -0.2 to -0.3 for New Zealand (Best and Burke (2019)) and -0.2 for Australia (Burke and Teame (2018)).

In a dynamic urban model, Avner, Rentschler, and Hallegatte (2014) examine the impact of carbon taxes on urban mobility and underline the lock-in effect from public transport investments: while the quality of urban transport infrastructure is difficult to capture quantitatively, we include data on satisfaction with public transport in our elasticity estimation to account for this effect.

7.3.4 Road damage

Road damage depends strongly on road usage (Jacobson and Wågberg (2005)), but not all vehicles affect road damage equally: wear and tear on the pavement is a rapidly rising function of a vehicle's axle weight (Jacobson and Wågberg (2005); Murphy and Delucchi (1997); Parker and Hussain Ph D (2006); FHWA (2000)). Estimations suggest that the pavement wear and tear of one average five-axle truck equates to approximately 4,000 cars (Freight & Infrastructure (2014)). Therefore, nearly all of the vehicle-caused road damage is attributable to heavy-duty vehicles (trucks).

In most countries around the world,¹ light-duty vehicles (cars) use gasoline and trucks use diesel. Road damage is thus more dependent on diesel price than on gasoline price.

The externality cost of road transport from pavement wear and tear has been discussed extensively in the economics literature, going back as far as Adam Smith (Lindsey (2006)). There is a consensus that diesel is strongly under-taxed, when comparing tax level to externality cost (Parry (2008); Santos (2017)).

Many authors have suggested addressing it directly through different forms of road pricing explicitly indexed on road damage cost (e.g. Newbery (1988); Parker and Hussain Ph D (2006); Santos et al. (2010)). From an economist's point of view, addressing the externality explicitly, with taxes mirroring the externality cost directly, is the first best solution. However, as a carbon tax also increases diesel prices, it decreases truck VKT and thereby reduces road damage (Barla, Gilbert-Gonthier, and Kuelah (2014); ; Wadud (2016)). In general, a carbon tax reduces all road transport externalities that depend on VKT (Ekins (1996)).

¹A notable exception are some European countries with high shares of light-duty vehicles running on diesel.

The strength of this co-benefit depends on the elasticity of truck VKT with respect to fuel prices/taxes. There is large evidence that trucks reduce their VKT when fuel prices rise. Let us cite just a few recent studies finding significantly elastic VKT for trucks: Barla, Gilbert-Gonthier, and Kuelah (2014) find short and long-run price elasticities of -0.43 and -0.80 respectively; He (2015) estimates a VKT elasticity of -0.54; Ramli and Graham (2014) estimate short-run price elasticity between -0.11 and -0.16, long-run elasticity between -0.21 and -0.30 for trucks; Leard et al. (2015) find estimates around -0.20.

Some studies find that the elasticity depends on the type of trucks: Wadud (2016) finds that rigid trucks show statistically significant price elasticity, but articulated trucks do not respond to changes in fuel prices.

On the opposite, some authors find that trucks are relatively inelastic with regards to fuel prices (Winebrake et al. (2015)). One study finds that higher diesel prices are associated with fewer but heavier trucks, and therefore *more* road damage (Cohen and Roth (2017)).

In practice, two cost components to road damage may arise: the cost of repairing the pavement damage, and the additional cost to users, which result from traveling on damaged roadways. Given the difficulty to measure the second component, we concentrate on the first component in CPAT.

Methodologically, it is important to note that some countries earmark revenues from fuel taxes or road charges for road maintenance (Gultom et al. (2017)). In these countries, our estimation technique is not valid because of endogeneity, so that we exclude them.

Quantitatively, road damage may be considered the smallest of the three transport externalities considered here.

7.3.5 Within-country heterogeneity (by socio-demographic characteristics)

Regarding the within-country heterogeneity of the effect of fuel price on VKT, the literature has not reached a consensus. Within countries, Bastian and Borjesson (2014) find that urban populations, in particular those with low incomes, respond stronger to fuel price increases and economic downturn, i.e. are reducing car travel more. Similarly, many studies find that (absolute) elasticity diminishes with higher income levels (Santos and Catchesides (2005); Small and Van Dender (2007); West (2017)). On the opposite, Wang and Chen (2014) find that higher income households show greater fuel price elasticity than lower income households.

Regarding the effect of fuel prices on accident fatalities, the literature suggest that the poor are more often victims of road accidents because of the vehicles they travel in. There is evidence that larger vehicles (in particular light trucks and SUVs) cause more fatalities than light passenger vehicles, while drivers of SUVs are relatively more protected: (White (2004)) calls this disequilibrium “the ‘Arms race’ on American roads”. The highest risk is borne by motorcycle riders who tend to have lower incomes than four-wheeled vehicle drivers (Hyatt et al. (2009)). A particular group at high risk for road death are young drivers (aged 15–24) and

their passengers. As these drivers are more sensitive to fuel prices, the young drivers accident rate responds particularly strongly to fuel price increases (Morrisey and Grabowski (2011)). One of the few studies looking at gender and race, Chi et al. (2010) find that fuel prices affect accident rates similarly for men and women, as well as for white and black population.

7.3.6 Between-country heterogeneity

Regarding the between-country heterogeneity of the effect of fuel prices on VKT, most estimates concentrate on developed countries, in particular the USA. Studies on developing countries often face data challenges, but so far the literature suggests that the elasticities lay within the same order of magnitude in developed and developing countries (Gillingham, Rapson, and Wagner (2016)).

Regarding the effect of fuel prices on accident fatalities, some studies look at differences between high- and low-income countries, but the literature on within-country determinants of road fatalities and their elasticity wrt to fuel prices is scarce. Data is notoriously more scarce in developing countries. Country-level panel data identification strategies such as used in Burke and Nishitateno (2015) typically yield one elasticity for all countries. A priori, the effect is unclear: wealthier individuals travel larger distances and thus have a higher risk of traffic accidents, but poorer individuals travel more on foot and on motorcycles, which increases their risk to die from a road accident.

7.3.7 Fuel prices vs. taxes

Most of the above mentioned literature examines the effect of fuel prices on the various outcomes discussed. However, for CPAT we are interested in the effect of a carbon tax.

Regarding the effect on VKT, Li, Linn, and Muehlegger (2014) show that gasoline consumption responds more strongly to gasoline taxes than to gasoline prices. They explain that consumers may respond more to taxes than equal-sized changes in tax-inclusive gasoline prices because of perceived persistence and salience. Variation in gasoline taxes also is covered much more intensively in the media.

Regarding road fatalities, Leigh and Wilkinson (1991) show that gasoline taxes have a significant effect on fatalities while the effect of price effect from oil market fluctuations is not significant. However, these findings are on a cents-per-liter basis rather than a percent basis, so they are not directly comparable to our results.

7.3.8 Methodology

Literature generally finds that the short-term elasticity of fuel use is weaker than the long-term elasticity wrt fuel prices (Chi et al. (2010)). Usually, researchers explain this finding by structural adjustments to the vehicle fleet, travel demand (work and residence locations) and infrastructure. Hence, there has been some methodological effort to estimate short-run and long-run elasticities separately.

The methodology for elasticity estimation in the Road Transport Module is similar to Burke and Nishitatenno (2015). Using country-year-level data, the main estimations are fixed effects and between estimators of a linear log-log equation. The between estimator uses average data for each country and provides estimates of long-run effects (Badi Hani Baltagi and Baltagi (2008); Badi H. Baltagi and Griffin (1984b); M. Hashem Pesaran and Smith (1995b); Pirotte (1999); Stern (2010)). Fixed-effects estimations control for time-invariant factors such as the extent of mountainous terrain, but when a static fixed-effects equation is estimated the coefficients represent short-run effects. This method has been widely used in the literature looking at the effect of fuel prices on road safety (Best and Burke (2019); Burke and Nishitatenno (2015); Grabowski and Morrissey (2006); Montour, 2011). An alternative way of estimating long-run elasticities is the distributed lag specification (Burke and Nishitatenno (2015); Chi, Porter, et al. (2013); Montour (2011)).

Other studies, e.g. Chi, Quddus, et al. (2013), use more time-series related methods, in particular testing for unit roots and accounting for stationarity. These methods are difficult to implement with unbalanced panels, as in our case. However, in his standard econometrics textbook (Badi Hani Baltagi and Baltagi (2008); Badi H. Baltagi and Griffin (1984b)) considers that time-series methods should apply when T (the number of periods) is large and N (the number of countries) is small, whereas panel data methods like the between estimator are appropriate when T small and N large: “Using panel data, one can avoid the problem of spurious regression... Unlike the single time series spurious regression literature, the panel data spurious regression estimates give a consistent estimate of the true value of the parameter as both N and T tend to ∞ . This is because, the panel estimator averages across individuals and the information in the independent cross-section data in the panel leads to a stronger overall signal than the pure time series case.”

7.4 Data sources

7.4.1 General

We use a panel dataset of country-year-level data, including as many countries and years as available, resulting in an unbalanced panel. The dataset covers the time from 1994 to 2021 and 186 countries around the world.

The main data source are the World Road Statistics (WRS), regularly published by the International Road Foundation (International Road Federation (2018b)). We use data from its editions 2001 to 2021, covering the years 1995 to 2019.

Aside many of our covariates, WRS also contains two of our outcomes of interest: we use total distance driven in vehicle-kilometers traveled (VKT) and road damage, as measured by infrastructure maintenance investment.

General demographic and macroeconomic variables are provided by the World Bank's World Development Indicators (WDI) database.² The World Bank's World Governance Indicators (WGI) database³ gives indicator measures of corruption and rule of law.

The online database for Sustainable Development Report (SDR) 2019⁴ (Sachs et al. (2019)) gives an indicator of the quality of public transport.

Weather information at the country-year level is provided by the Climatic Research Unit (CRU) of the University of East Anglia, downloadable via the World Bank's Climate Change Knowledge Portal (CCKP).⁵ We use the precipitation (in mm), the minimum temperature (in °C), the number of hot days ($T_{max} > 40^{\circ}\text{C}$), and the number of ice days ($T_{max} < 0^{\circ}\text{C}$).

All monetary variables are deflated to 2018 USD using the World Bank's US GDP deflator and adjusted for purchasing power parity (WDI).

An exhaustive list of variables with their sources can be found in Section 7.10.1.

7.4.2 Congestion

Traffic congestion is measured using the TomTom Traffic Index. This index covers over 400 cities across 61 countries. The TomTom Traffic index statistics are calculated from anonymized GPS data collected via navigation devices, in-dashboard systems and smartphones.

The congestion level percentages represent the measured amount of extra travel time experienced by drivers across the entire year. As a first step, TomTom establishes a baseline of travel times during uncongested, free flow conditions across each road segment in each city. They then analyze travel times across the entire year for each city. The TomTom Traffic Index then represents the difference between observed travel times and free flow travel time.

For example, an overall congestion level of 36% means that the extra travel time is 36% more than an average trip would take during uncongested conditions. Average times are of actual taken trips, across every vehicle in the entire network, 24/7. Travel times in free-flow (uncongested) conditions are not based on legal speed limits but on actual trips made.

²<https://databank.worldbank.org/reports.aspx?source=world-development-indicators>

³<https://datacatalog.worldbank.org/dataset/worldwide-governance-indicators>

⁴<https://dashboards.sdgindex.org/>

⁵<https://climateknowledgeportal.worldbank.org/>

The TomTom Traffic Index is available both overall, as well as for specific weekdays and peak times, including morning and evening peak hours.

7.4.3 Road safety

The United Nations Economic Commission for Europe (UNECE)⁶ and the Organization for Economic Co-operation and Development (OECD)⁷ provide statistical databases, used to complete missing data points in the WRS, in particular for accident fatalities.

The World Health Organization (WHO) publishes reports on Road Safety. We use the 2013 edition with data on 2011 (World Health Organization and others (2013)) and the 2018 edition with data on 2017 (World Health Organization (2018b)), which include detailed covariates on the legal framework of traffic, such as seat belt wearing rate, blood alcohol concentration limit, helmet enforcement and others.⁸

For Côte d'Ivoire and Mexico, country-specific projects made more detailed accident data available, which are included in the general CPAT analysis. Missing data for Côte d'Ivoire in WRS are completed using the national accident statistics provided by the Ivorian Ministry of Transport. Unrealistically low accident numbers for Mexico in WRS are replaced by data from the Mexican National Institute of Statistics and Geography (INEGI) and the Mexican Transport Institute (IMT).

7.4.4 Fuel prices

Fuel prices are taken from the fuel price database of the overall CPAT project. For road fuels, the sources used are the IMF's Fiscal Affairs Department (FAD), Enerdata's Global Energy and CO2 Data, IEA's Data and statistics and GIZ's Sustainable Urban Transport Project.

In combining these different data sources, the following order of steps is applied:

1. If Enerdata, IEA and IMF data is available, we establish a weighted average of price data in Enerdata (60%), IEA (10%) and IMF (30%);
2. if IMF or IEA are missing, we use Enerdata;
3. If Enerdata is missing, we use the information in the IMF database;
4. If IMF is missing, we use the information in the IEA database;
5. If IEA is missing, we use the information in the GIZ database.

⁶<https://w3.unece.org/PXWeb/en>

⁷<https://data.oecd.org/transport/road-accidents.htm>

⁸Unfortunately, the WHO uses another definition of road accident deaths than WRS data, so that aggregate numbers of fatalities are not comparable.

Aside the final retail price at the pump, we use data on taxes summarizing VAT, existing carbon taxes, excise tax and others. We use the same algorithm as described above for prices to construct time series of fuel taxes. Supply cost is defined as the difference of price at the pump minus taxes.

7.4.5 Externality costs

The benefits of prevented mortalities can be expressed in terms of a “Value of a Statistical Life” (VSL), which represents the value a given population places *ex ante* on avoiding the death of an unidentified individual. VSL is based on the sum of money each individual is prepared to pay for a given reduction in the risk of premature death, for example from diseases linked to air pollution OECD (2012).

The country-specific VSL in CPAT is adapted from OECD (2012), adjusted for GDP growth and inflation (within the Air Pollution Module).

We compute the average speed from TomTom’s total VKT and total travel time. We then compute the VKT per capita from WRS’ national VKT divided by the population size from the WB’s World Development Indicators (WDI). This average VKT per capita is multiplied by the size of urban population over 15 year of age (WDI) and divided by the average speed, yielding total urban travel time.

The total urban travel time is then multiplied by 80% of the average hourly after-tax wages (from Air Pollution Module), yielding the value of travel time.

7.4.6 Data cleaning

Several variables result of the combination of several data sources. For example, we combine information on accident fatalities from WRS, OECD and UNECE. In these cases, we define a clear order and only “fill up” missing variables with the second and third source.

After establishing this mix of data sources, a visual control of country-specific time series is performed to identify outliers. For each visually identified outlier, we perform thorough background checks and in case of doubt only keep one source (resulting in some limited data loss).

Stock variables such as length of road network, country area or size of population are interpolated linearly when missing between years with non-missing data for that country. However, we do not extrapolate beyond the last/first year with non-missing data. The variable table in Section 7.10.1 indicates for which variables such interpolation is performed.

7.5 Methods for elasticity estimation

This chapter explains the general methodology for estimating short- and long-run elasticities and making them country-specific in a data-parsimonious way. This methodology is then applied to VKT and the three outcomes of interest: congestion, road damage and fatalities from road accidents.

7.5.1 Estimation equation

We regress the logarithm of the outcome variable onto a constant, the logarithm of fuel prices, a list of covariates and fixed effects. The general form of the estimated regression estimation is

$$\ln(Y_{ct}) = \alpha + \beta \ln(p_{ct}) + \gamma X_{ct} + \mu_t + \mu_c + \epsilon_{ct} \quad (7.1)$$

Where $\ln(Y_{ct})$ is the natural logarithm of the outcome in country c in year t , $\ln(p_{ct})$ is the natural logarithm of pump price for gasoline, X_{ct} is a vector of covariates including income per capita and population density, and μ_c and μ_t are country- and year-specific effects.

An elasticity measures how much an outcome changes relatively to its initial value (e.g. in percent) when another variable, here the pump price of gasoline, changes (in percent). As we are using the log-log specification, the coefficient estimate $\hat{\beta}$ in Equation 7.1 is an estimate of the elasticity of the outcome Y_{ct} with respect to (wrt) fuel prices p_{ct} .

7.5.2 Short-run and long-run estimators

Following Burke and Nishitatenno (2015), we consider that the within estimator from a static fixed-effects equation represents shorter-run effects, and the between estimator provides estimates of long-run effects (Badi Hani Baltagi and Baltagi (2008); Badi H. Baltagi and Griffin (1984b); M. Hashem Pesaran and Smith (1995b); Piroette (1999); Stern (2010)).⁹

For simplicity, let us reduce the notation of the previous equation (Equation 7.1) to:

$$y_{ct} = \alpha + \beta x_{ct} + \mu_c + \epsilon_{ct} \quad (7.2)$$

Where the logarithms have been omitted and all righthand-side variables summarized under the vector x_{ct} .

⁹(Burke & Nishitatenno, 2015) use both between estimator (as described here) and a distributed lag specification to estimate long-run elasticities of road fatalities wrt fuel prices. Both methodologies yield very similar results in their case. In the data used here, the number of distributed lags to be included seems difficult to establish and the results do not appear very consistent.

The interpretation for the long and short run is based on the idea that the previous Equation 7.2 may alternatively be formulated:

$$y_{ct} = \alpha + \beta' \bar{x}_c + \beta''(x_{ct} - \bar{x}_c) + \mu_c + \epsilon_{ct} \quad (7.3)$$

Where \bar{x}_c is the average of x_{ct} over time: $\bar{x}_c = \sum_t x_{ct}/T_c$, where T_c is the number of years included for country c in the regression.

In the model described by Equation 7.3, we postulate that changes in the average value of x_{ct} for an individual country may have a different effect from temporary departures from the average. The model allows a different response to permanent rather than transitory changes. If $\beta' = \beta''$, then the model in Equation 7.3 collapses into the previous model in Equation 7.2.

Whatever the properties of μ_c and ϵ_{ct} , if Equation 7.2 is true, we can take the averages and find that:

$$\bar{y}_c = \alpha + \beta' \bar{x}_c + \mu_c + \bar{\epsilon}_c \quad (7.4)$$

where \bar{y}_c is the average of y_{ct} over time: $\bar{y}_c = \sum_t y_{ct}/T_c$ and $\bar{\epsilon}_c$ is the average of the error term: $\bar{\epsilon}_c = \sum_t \epsilon_{ct}/T_c$.

Subtracting Equation 7.4 from Equation 7.3, it must also be true that:

$$y_{ct} - \bar{y}_c = \beta''(x_{ct} - \bar{x}_c) + (\epsilon_{ct} - \bar{\epsilon}_c) \quad (7.5)$$

These equations are known from panel econometrics textbooks: Equation 7.4 describes the between estimator and Equation 7.5 describes the within estimator, also known as fixed-effects estimator.

Fixed-effects estimations control for time-invariant characteristics of countries such as the extent of size or mountainous terrain. As illustrated in Equation 7.5, the identifying variation comes from within-country deviations from the country-mean. Given standard assumptions on the error term ϵ_{ct} (mean 0, uncorrelated with itself, uncorrelated with x_{ct} , uncorrelated with μ_c , and homoscedastic), the within estimator can be estimated as an OLS on Equation 7.5 or, equivalently, an OLS on Equation 7.1 including country dummy variables. For this study, this equation is estimated using the Stata command *xtreg, fe*.

The between estimator is given by the OLS estimator on Equation 7.4. This specification cancels out time-differences. The between estimates are based on cross-sectional country differences. Individual-invariant regressors such as time dummies cannot be identified. For this project, this equation is estimated using the Stata command *xtreg, be*.¹⁰

¹⁰See the Stata 15 longitudinal data/panel-data reference manual for more details (Stata Press, 2017).

7.5.3 Covariates

The choice of the variables used as covariates X_{ct} follows the list of variables used in World Health Organization (2018b). A detailed list can be found in Section 7.10.1.

7.5.4 Country-specific elasticity estimates

The effect of fuel prices on our three outcomes of interest is likely to be heterogeneous across different countries. However, there is limited data available for most countries, so that unparametrically country-specific estimations proved not feasible. We discard the option to create *ad hoc* regional groups and estimate group-specific elasticities, as we want a more data-driven methodology. To strike a balance between accounting for heterogeneity and using available data parsimoniously, we estimate elasticities that are linear expressions of several covariates.

The estimation includes interaction terms between fuel prices and the additional variables. For example, if elasticity depends on two more variables, the estimation equation is:

$$\ln(Y_{ct}) = \alpha + \beta_0 \ln(p_{ct}) + \beta_1 v_{ct}^1 \ln(p_{ct}) + \beta_2 v_{ct}^2 \ln(p_{ct}) + \gamma X_{ct} + \mu_c + \mu_t + \epsilon_{ct} \quad (7.6)$$

where the variables are the same as before, and v_{ct}^1 is the first additional variable influencing elasticity and v_{ct}^2 is the second additional variable influencing elasticity. The “country-specific” elasticity estimated is then:

$$\hat{\beta}_c = \hat{\beta}_0 + \hat{\beta}_1 \overline{v_c^1} + \hat{\beta}_2 \overline{v_c^2} \quad (7.7)$$

where $\overline{v_c^1}$ is the average across recent years¹¹ of variable v_{ct}^1 for country c (and analogously for variable $\overline{v_c^2}$). In practice, we include not two but five additional variables v_{ct}^k , which we omit here for readability.

We consider 15 candidate variables linked to traffic conditions, demographics and availability of substitutes to private vehicles. The final estimations include only the variables found to be empirically most important.

The selection of covariates v_{ct}^k included in the expressions of elasticities is data-driven using a lasso regression as implemented in Stata command *lasso2* (Ahrens, Hansen, and Schaffer (2020)). The lasso procedure penalizes additional variables/parameters and thereby encourages simple, sparse models, i.e. models with fewer parameters. The algorithm sequentially includes one variable after the other, in an optimized order. The order in which predictors are entered into the model can be interpreted as an indication of the relative predictive power of each predictor.

¹¹In our calculations, “recent” has been defined as the country average over the five most recent available years of a given variable.

7.5.5 Fuel prices or taxes

We are interested in the effect of carbon taxes on accidents. The most classical way of estimating tax impact consists in estimating price elasticity from exogenous price variation. However, some of the literature states that consumers might not react identically to price changes and to tax changes (salience, anticipation of persistence over time).

Therefore, we estimate two sets of elasticities: elasticities wrt fuel prices and wrt fuel taxes. The estimation for elasticity wrt to prices follows the equations above. The estimations for elasticity wrt to taxes include the natural logarithms of both tax-exclusive prices and taxes as two separate variables. The elasticity of interest is then the estimated coefficient of the tax variable. Fuel tax data is only available for a limited amount of countries.

7.6 Elasticity results

For readability, this note includes shortened results tables. For the full results, please refer to the *Tran_Elas* sheet of CPAT.

7.6.1 Congestion

Figure 7.4 shows descriptive evidence of the relationship between urban congestion and gasoline prices: across countries, there is a significant negative correlation in 2018.¹² Congestion is measured with the TomTom Traffic Index, indicating the additional time spent in congested traffic as compared to free-flowing traffic (in percent, see Section 7.4.2 for more details).

This simple descriptive evidence omits many variables. In particular, the elasticity of demand of private vehicle trips depends on the availability of (and practicability) alternative means of transport. Moreover the resulting congestion depends on whether these alternative means of transport will also be on the road (e.g. buses) or elsewhere (e.g. trains).

Source: Tomtom, Enerdata, EIU, IEA, own computations.

7.6.1.1 Short-run elasticity

This section shows the results for the short-run estimations of congestion on fuel prices and a list of covariates. The most relevant specification is the within estimator of Equation 7.1, as specified in Equation 7.5.

For simplicity, we only show the regression results for overall congestion, whereas CPAT also contains estimates for weekday congestion and weekday peak time congestion. The results

¹²Including all country-years results in an overcrowded unreadable graph, but the negative relationship persists.

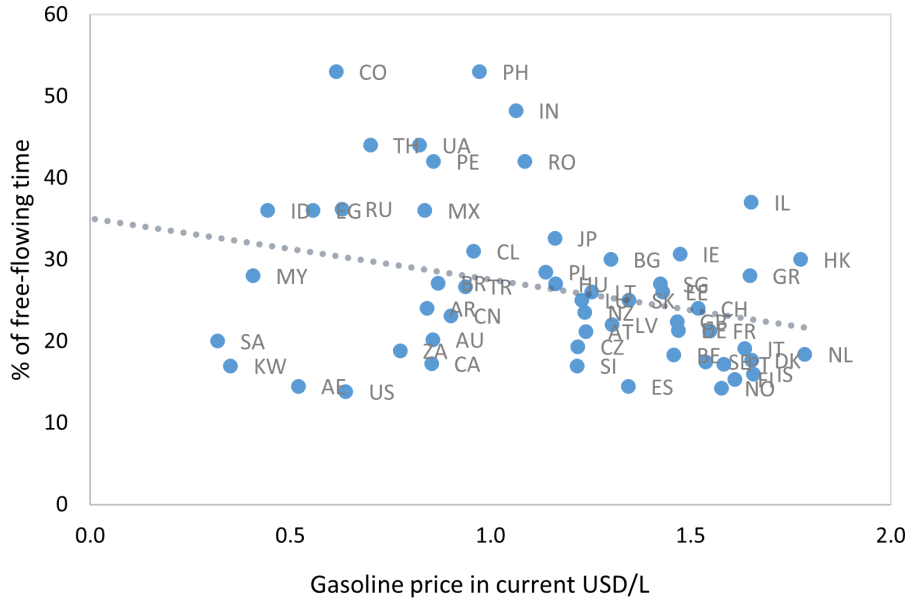


Figure 7.4: Scatter plot and linear regression of urban congestion as a function of gasoline prices in 2020

on these three indicators are similar, but the effect on peak congestion is typically slightly stronger.

Table 7.2: Regression results short-run congestion

Urban congestion	(1)	(2)	(4)	(3)	(5)	(6)
	pooled within					
	OLS					
	Se-					
	ti-					
	ma-					
	tor					
Ln of gasoline pump price (2018 PPP-adj USD cents/liter)	0.0189	-	-	-	-	-
	0.0776	0.330	0.149	0.288	0.503	0.503
	(0.584)	(0.0799)	(0.200)	(0.620)	(0.00171)	(0.00171)
Interaction ln(gasoline) w/ Ln of number of vehicles per capita			0.312**		0.294**	
			(0.0153)		(0.0454)	
Interaction ln(gasoline) w/ Precipitation (in mm)			0.207***		0.103**	
			(2.05e-05)		(0.0107)	

Urban congestion	(1)	(2)	(4)	(3)	(5)	(6)
Interaction ln(gasoline) w/ Satisfaction with public transport (%)			-		-	
			0.0106		0.0322***	
			(0.667)		(0.00398)	
Interaction ln(gasoline) w/ Share of paved roads (in %)			-		-	
			0.0477*		0.116	
			(0.0555)		(0.239)	
Interaction ln(gasoline) w/ Ln of population			0.171***		0.0536	
			(0.00205)		(0.439)	
Covariates	No	Yes	Yes	No	Yes	Yes
Fixed effects	No	No	No	Yes	Yes	Yes
Interaction terms	No	No	Yes	No	No	Yes
Observations	583	467	467	583	467	467
R-squared	0.287	0.495	0.550	0.214	0.384	0.415
Number of countries				61	52	52

*Robust p-values in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Ln(gasoline) is the natural logarithm of the gasoline pump price (2018 PPP-adjusted USD cents/liter). The parameter marked in green is the default short-run elasticity in CPAT for countries that have not sufficient data for country-specific elasticity estimation. Sample averages are subtracted from the interaction variables prior to interacting with the fuel price.*

Table 7.2 shows results of the pooled OLS (column 1-3) and within estimator (column 4-6). For each estimator, we compute the coefficient first without and then with covariates included. All of the estimates lie within a similar order of magnitude: the short-run elasticity of congestion wrt fuel price is estimated between -0.08 and -0.29. This is very close to the estimates ranging from -0.12 to -0.29 in Burger and Kaffine (2009) and more inelastic than the estimate of -0.35 in Dahl (1979).

The columns 4 and 6 show the results of including additional interaction terms between the fuel price and selected variables. The coefficient of the fuel price is not directly interpretable in this specification. In order to obtain country-specific elasticity estimates, one needs to multiply the coefficients with the country-specific values of the covariates. The results are given below in Section 7.6.1.3.

7.6.1.2 Long-run elasticity

Computing the between estimator of Equation 7.1, given by Equation 7.4, we obtain the long-run elasticity.

Table 7.3: Regression results long-run congestion

Urban congestion	(1)	(2)	(4)
		between	
		es-	
		ti-	
		ma-	
		tor	
Ln of gasoline pump price (2018 PPP-adj USD cents/liter)	-	-	-
	0.1250	0.3647	0.707
	(0.00436)	(0.214)	(0.08)
Interaction ln(gasoline) w/ Maximum speed on urban roads (in km/h)			0.260
			(0.129)
Interaction ln(gasoline) w/ Precipitation (in mm)			0.0821
			(0.421)
Interaction ln(gasoline) w/ Seat-belt wearing rate (%)			-
			0.105
			(0.326)
Interaction lnsuper w/ Infant mortality rate (per 1,000 live births)			-
			0.906**
			(0.0394)
Interaction ln(gasoline) w/ Ln of population			-
			0.0210
			(0.934)
Covariates	No	Yes	Yes
Interaction terms	No	No	Yes
Observations	583	467	467
R-squared			0.786
Number of countries	61	52	52

*Robust p-values in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Ln(gasoline) is the natural logarithm of the gasoline pump price (2018 PPP-adjusted USD cents/liter). The parameter marked in green is the default long-run elasticity in CPAT for countries that have not sufficient data for country-specific elasticity estimation. Sample averages are subtracted from the interaction variables prior to interacting with the fuel price.*

Again, the first two columns of Table 7.3 show the estimates first without and then with covariates included into the regression. The third column shows the results of including the interaction of fuel price with the empirically relevant covariates, which are not directly interpretable and will be discussed in the next subsection.

7.6.1.3 Country-specific elasticities

Table 7.2 and Table 7.3 show the results of regressing congestion on fuel prices and covariates, estimating the short-run (within estimator) and long-run (between estimator) elasticities. The parameters of the last column of each table give the results of including interaction terms with relevant covariates, as described by Equation 7.6. The most relevant interaction terms are chosen using lasso regressions (see Section 7.3.8 for methodology).

While using fuel price data for estimating elasticity is standard in the literature, some authors have suggested that consumers react more strongly to changes in fuel taxes than to (equivalent) changes in fuel prices. This hypothesis typically relies on additional salience of taxes, which are often strongly featured in the media, and on expectations about the persistence of the price change into the future.

Therefore, we repeat the same estimations of Table 7.2 and Table 7.3 using fuel supply cost and fuel taxes as two separate variables, rather than overall fuel price at the pump. Detailed results are omitted here, but can be found in the MS Excel file appendix to this report.

As a result, we have four elasticity estimates for each country: short-run and long-run, each wrt prices and wrt taxes.

Table 7.4 shows the lists of variables which are selected by the lasso regression algorithm as the five most relevant covariates for fuel price elasticity of congestion. The elasticities depend on characteristics of the vehicle fleet (number of vehicles per capita, share of motorcycles), on characteristics of the road network (density, speed limits), characteristics of transport substitutes (satisfaction with public transport) and on more general features of society (population size, rule of law indicator, urbanization, share of young people, and others).

Table 7.4: Variables selected for country-specific congestion elasticity estimation

Short run	Long run		
wrt price	wrt tax	wrt price	wrt tax
Ln of number of vehicles per capita	Number of vehicles per capita	Maximum speed on urban roads (in km/h)	Maximum speed on urban roads (in km/h)
Satisfaction with public transport (%)	Satisfaction with public transport (%)	Ln of population	Ln of population

Short run	Long run		
Share of paved roads (in %)	Share of urban population (in %)	Infant mortality rate (per 1,000 live births)	Infant mortality rate (per 1,000 live births)
Ln of population	Seat-belt wearing rate (%)	Seat-belt wearing rate (%)	Satisfaction with public transport (%)
Precipitation (in mm)	Maximum speed on urban roads (in km/h)	Precipitation (in mm)	Road density (in km per km ²)

Notes: The covariates used for estimating the country-specific elasticities are chosen by a data-driven machine learning algorithm among a list of 30 candidate variables.

Given the large number of countries and variants, the elasticities are not reproduced here. The detailed numbers can be found in CPAT or in the MS Excel appendix to this report.

Figure 7.5 shows the kernel densities¹³ of the congestion elasticity estimates in the short and the long-run, wrt fuel price and wrt fuel tax. One can see that congestion is more elastic to fuel prices in the long run than in the short run. This is a classical result, as consumers have the possibility to adjust more in the long run than in the short run.

Table 7.5 summarizes the key characteristics of the distributions shown in Figure 7.5: mean, median, 5th and 95th percentiles of the distribution.

Table 7.5: Country-specific congestion elasticities, numerical overview

Urban congestion	Short-run		Long-run	
	wrt price	wrt tax	wrt price	wrt tax
Default elasticity	-0.288	-0.118	-0.364	-0.119
Mean	-0.339	-0.305	-0.807	-0.612
Median	-0.340	-0.296	-0.798	-0.531
5th percentile	-0.433	-0.381	-1.001	-1.127
95th percentile	-0.242	-0.229	-0.667	-0.294
Number of estimates	158	151	174	154

¹³Produced using Stata's *kdensity* command.

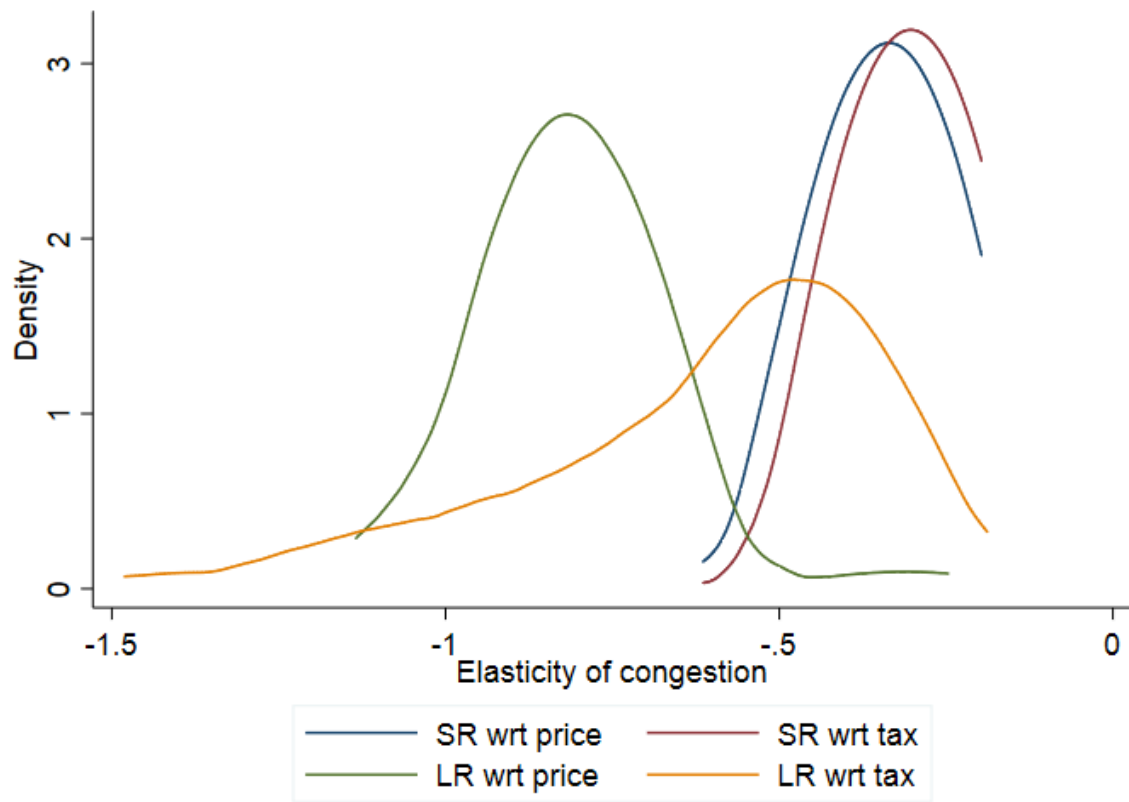


Figure 7.5: Country-specific congestion elasticities, graphical overview

7.6.2 Fatalities from road accidents

For illustration, Figure 7.6 shows descriptive evidence of the negative correlation between fuel prices and road accident fatalities. The higher the gasoline price the lower the accident fatality rate per 100,000 inhabitants.

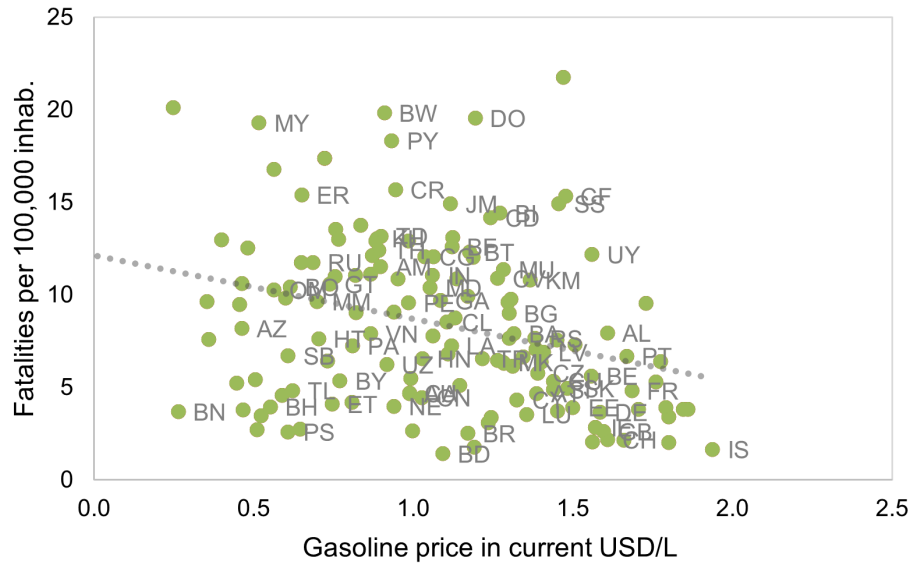


Figure 7.6: Scatter plot and linear regression of country-level road fatalities as a function of gasoline prices in 2019

Source: WRS, Enerdata, EIU, IEA, own computations.

7.6.2.1 Short-run elasticity

This section shows the results for the short-run estimations of road accident fatalities on fuel prices and a list of covariates, following the general form of Equation 7.1.

Table 7.6: Regression results short-run accident fatalities

Accident fatalities	(1)	(2)	(4)	(3)	(5)	(6)
	pool within OLSes- ti- ma- tor					
Ln of gasoline pump price (2018 PPP-adj USD cents/liter)	-	-	-	-	-	-
	0.118***	0.112***	0.112***	0.112***	0.112***	0.112***
	(1.41e-07)	(1.00e-06)	(1.23e-06)	(1.14e-06)	(1.86e-07)	(1.68e-06)
Interaction ln(gasoline) w/ Road density (in km per km2)			0.324**			-
			(0.0333)			0.533***
Interaction ln(gasoline) w/ Population share of 15 to 24 years-old (in %)			-			0.131***
			0.174***			(2.13e-05)
			(2.78e-07)			(2.13e-05)
Interaction ln(gasoline) w/ Seat-belt wearing rate (%)			-			0.0122
			0.0766***			(0.241)
			(2.12e-09)			
Interaction ln(gasoline) w/ Satisfaction with public transport (%)			-			-
			0.0766***			0.0111
			(1.06e-10)			(0.138)
Interaction ln(gasoline) w/ Number of vehicles per capita			-			-
			0.241***			0.127***
			(1.14e-08)			(0.00171)
Covariates	No	Yes	Yes	No	Yes	Yes
Fixed effects	No	No	No	Yes	Yes	Yes
Interaction terms	No	No	Yes	No	No	Yes
Observations	3,240	2,035	1,874	1,953	3,240	2,035
R-squared	0.860	0.905	0.930	0.907	0.202	0.287
Number of country FE				170	138	121

Robust p-values in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Ln(gasoline) is the natural logarithm of the gasoline pump price (2018 PPP-adjusted USD cents/liter). The parameter

marked in green is the default short-run elasticity in CPAT for countries that have not sufficient data for country-specific elasticity estimation. Sample averages are subtracted from the interaction variables prior to interacting with the fuel price.

The estimates for the short-run elasticity of accidents wrt fuel prices lie between -0.11 and -0.168 (Table 7.6, columns 1, 2, 4 and 5). Our estimates are similar to the short-run estimate of (Burke and Nishitatenno (2015)) with -0.10. The columns 3 and 6 include the interaction terms and are not directly interpretable; the resulting country-specific elasticities are discussed in Section 7.6.2.3.

7.6.2.2 Long-run elasticity

Table 7.7: Regression results long-run accident fatalities

Accident fatalities	(1)	(2)	(3)
			between
			es-
			ti-
			ma-
			tor
Ln of gasoline pump price (2018 PPP-adj USD cents/liter)	-	-	0.123
	0.214	0.192	***
	(0.032)	(0.018)	(0.432)
			09)
Interaction ln(gasoline) w/ Ln of number of vehicles per capita			-
			0.150
			(0.438)
Interaction ln(gasoline) w/ Alcohol, recorded per capita (15+) consumption (in litres)			0.179
			(0.210)
Interaction ln(gasoline) w/ Number of motorcycles per capita			0.0909
			(0.461)
Interaction ln(gasoline) w/ GDP per capita (in 2018 PPP-adj USD)			0.0124
			(0.936)
Interaction ln(gasoline) w/ Share of urban population (in %)			0.0690
			(0.465)
Covariates	No	Yes	Yes
Interaction terms	No	No	Yes
Observations	3,240	2,035	2,035
R-squared	0.880	0.900	0.919
Number of countries	170		138

Robust *p*-values in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. $\ln(\text{gasoline})$ is the natural logarithm of the gasoline pump price (2018 PPP-adjusted USD cents/liter). The parameter marked in green is the default long-run elasticity in CPAT for countries that have not sufficient data for country-specific elasticity estimation. Sample averages are subtracted from the interaction variables prior to interacting with the fuel price.

The long-run elasticity estimates in Table 7.7 lie between -0.19 and -0.21 (column 1 and 2). This is less elastic than the estimates of (Burke and Nishitatenno (2015)) with -0.30 to -0.60. The third column cannot be directly interpreted and is discussed in the following subsection.

7.6.2.3 Country-specific elasticities

Table 7.8 shows the lists of variables which are selected by the lasso regression algorithm as the five most relevant covariates for the elasticity of accident fatalities, chosen by a data-driven algorithm. Again, the elasticities depend on characteristics of the vehicle fleet, on characteristics of the road network and on more general features of society. In particular, motorcyclist are known to be at particularly high risk for accident injury and death. Classical road safety features such as seat-belt wearing rate, alcohol consumption and maximum speed allowed also play a role. More broadly, GDP and infant mortality rate capture the general development situation of the country, as well as the quality of the country’s health system.

Table 7.8: Variables selected for country-specific accident elasticity estimation

Short run	Long run		
wrt price	wrt tax	wrt price	wrt tax
Number of vehicles per capita	Ln of number of vehicles per capita	GDP per capita (in 2018 PPP-adj USD)	GDP per capita (in 2018 PPP-adj USD)
Population share of 15 to 24 years-old (in %)	Population share of 15 to 24 years-old (in %)	Alcohol, recorded per capita (15+) consumption (in litres of pure alcohol)	Alcohol, recorded per capita (15+) consumption (in litres of pure alcohol)
Satisfaction with public transport (%)	Infant mortality rate (per 1,000 live births)	Share of urban population (in %)	Share of urban population (in %)

Short run	Long run		
Road density (in km per km ²)	Number of motorcycles per capita	Ln of number of vehicles per capita	Number of motorcycles per capita
Seat-belt wearing rate (%)	Maximum speed on rural roads (in km/h)	Number of motorcycles per capita	Maximum speed on rural roads (in km/h)

Notes: The covariates used for estimating the country-specific elasticities are chosen by a data-driven machine learning algorithm among a list of 30 candidate variables.

Figure 7.7 shows the distribution of country-specific accident elasticity estimates. We see that both the long-run and short-run, as well as tax and price estimates are rather similar and lie between -0.2 and -0.8, thus comparable to the estimates of (Burke and Nishitatenno (2015)) with -0.3 to -0.6.

Table 7.9 summarizes the key characteristics of the distributions shown in Figure 7.7: mean, median, 5th and 95th percentiles.

Table 7.9: Country-specific accident elasticities, numerical overview

Accident fatalities	Short-run		Long-run	
	wrt price	wrt tax	wrt price	wrt tax
Default elasticity	-0.168	-0.150	-0.192	-0.137
Mean	-0.613	-0.536	-0.443	-0.357
Median	-0.603	-0.546	-0.432	-0.364
5th percentile	-0.741	-0.571	-0.514	-0.459
95th percentile	-0.532	-0.491	-0.373	-0.208
Number of estimates	151	160	169	158

7.6.3 Road damage

Road damage is measured in CPAT with the road infrastructure expenditure for maintenance, as listed in the WRS. The underlying hypothesis is that all road damage is repaired and therefore captured by the road maintenance budget of the government, as opposed to road investment for the expansion of the road network.

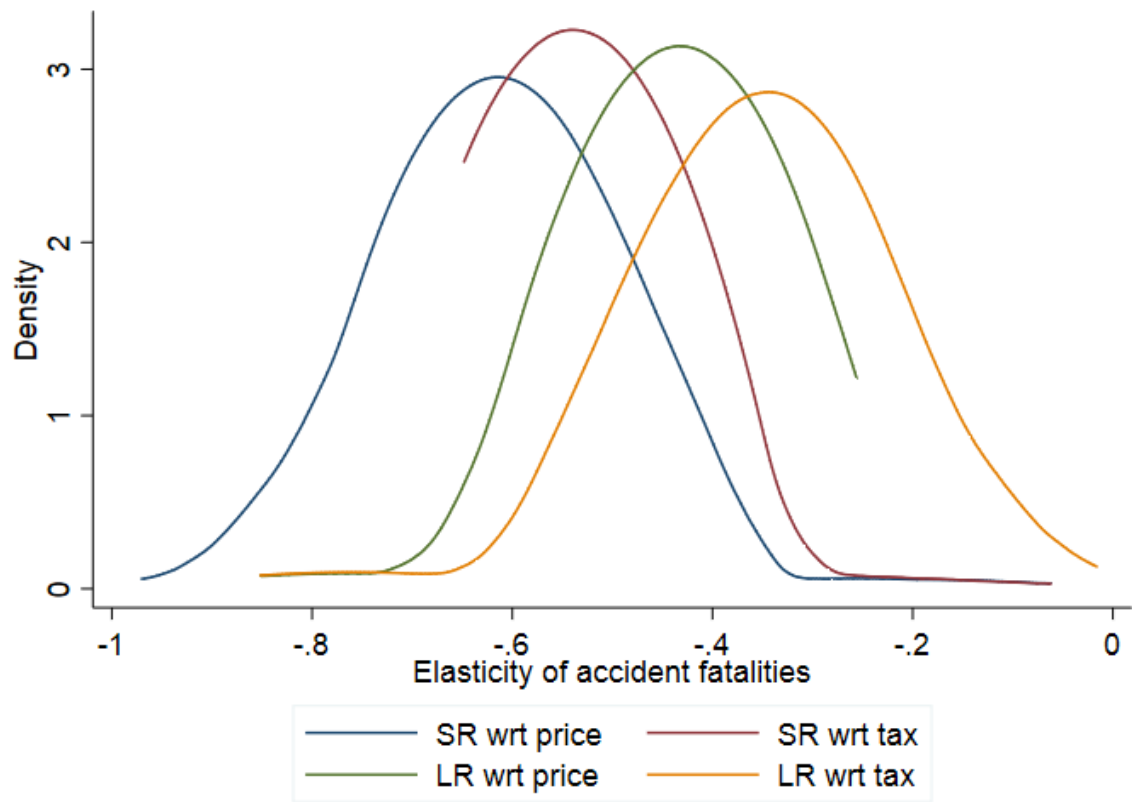


Figure 7.7: Country-specific accident elasticities, graphical overview

Compared to the other two outcomes previously discussed, road damage presents the particularity to be more dependent on diesel price than on fuel price. Although the differential impact of a carbon tax on fuel and gasoline prices is relatively small, we thus use diesel prices in this section rather than gasoline prices as before.

7.6.3.1 Short-run elasticity

The results of road damage in the short run are not significant. They are included in the MS Excel appendix to this report, but within CPAT we assume the short run elasticity of road damage wrt fuel prices to be zero.

7.6.3.2 Long-run elasticity

In the long run, road damage costs react to diesel prices, but the results are not statistically significant as shown in Table 7.10. In the simple specifications (columns 1 and 2), the elasticity is around -0.3. We use the parameters estimated in the specification including interaction terms (column 3) in order to compute the country-specific elasticities for CPAT presented in the next subsection.

Table 7.10: Regression results long-run road damage costs

Road damage	(1)	(2)	(3)
		between	
		es-	
		ti-	
		ma-	
		tor	
Lag of ln of diesel pump price (2018 PPP-adj USD cents/liter)	0.0957	0.819	
		0.269	
	(0.862)	(0.735)	(1.56)
Interaction ln(diesel) w/ Minimum of daily min-temperature (in B0C)		0.352	
		(0.397)	
Interaction ln(diesel) w/ Total length of road network (in km)		-	
		1.476***	
		(0.00177)	
Interaction ln(diesel) w/ Share of paved roads (in %)		-	
		0.947**	
		(0.0431)	
Interaction ln(diesel) w/ Share of urban population (in %)		0.391	
		(0.277)	
Interaction ln(diesel) w/ Number of lorries and vans		0.563	

Road damage	(1)	(2)	(3)
			(0.677)
Covariates	No	Yes	Yes
Interaction terms	No	No	Yes
Observations	1,321	1,039	1,039
R-squared	0.726	0.803	0.914
Number of countries	118	103	103

Robust *p*-values in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. $\ln(\text{diesel})$ is the natural logarithm of the gasoline pump price (2018 PPP-adjusted USD cents/liter). The parameter marked in green is the default long-run elasticity in CPAT for countries that have not sufficient data for country-specific elasticity estimation. Sample averages are subtracted from the interaction variables prior to interacting with the fuel price.

7.6.3.3 Country-specific elasticities

As shown on Table 7.11, the long-run road damage elasticities depend on structural features of the country's transportation system (population density, total road network, urbanization), on the vehicle fleet, particularly larger vehicles, and rule of law. Additionally, weather plays an important role for road damage. In particular, minimum temperatures seem to impact the effect of a carbon tax: with less traffic, the effect of low temperatures (frost) on road damage is reduced.

Table 7.11: Variables selected for country-specific road damage elasticity estimation

Long run	
wrt price	wrt tax
Number of lorries and vans	Number of lorries and vans
Total length of road network (in km)	Total length of road network (in km)
Share of urban population (in %)	Share of urban population (in %)
Share of paved roads (in %)	Road density (in km per km ²)
Minimum of daily min-temperature (in °C)	Population density (people per sq. km of land area)

Notes: The covariates used for estimating the country-specific elasticities are chosen by a data-driven machine learning algorithm among a list of 30 candidate variables.

Figure 7.8 shows that the estimates using fuel taxes suggest less elasticity of road prices wrt fuel taxes than the estimates using prices at the pump. Overall, virtually all estimates lie above -1, suggesting a less than one-to-one reaction of road damage to changes in fuel prices.

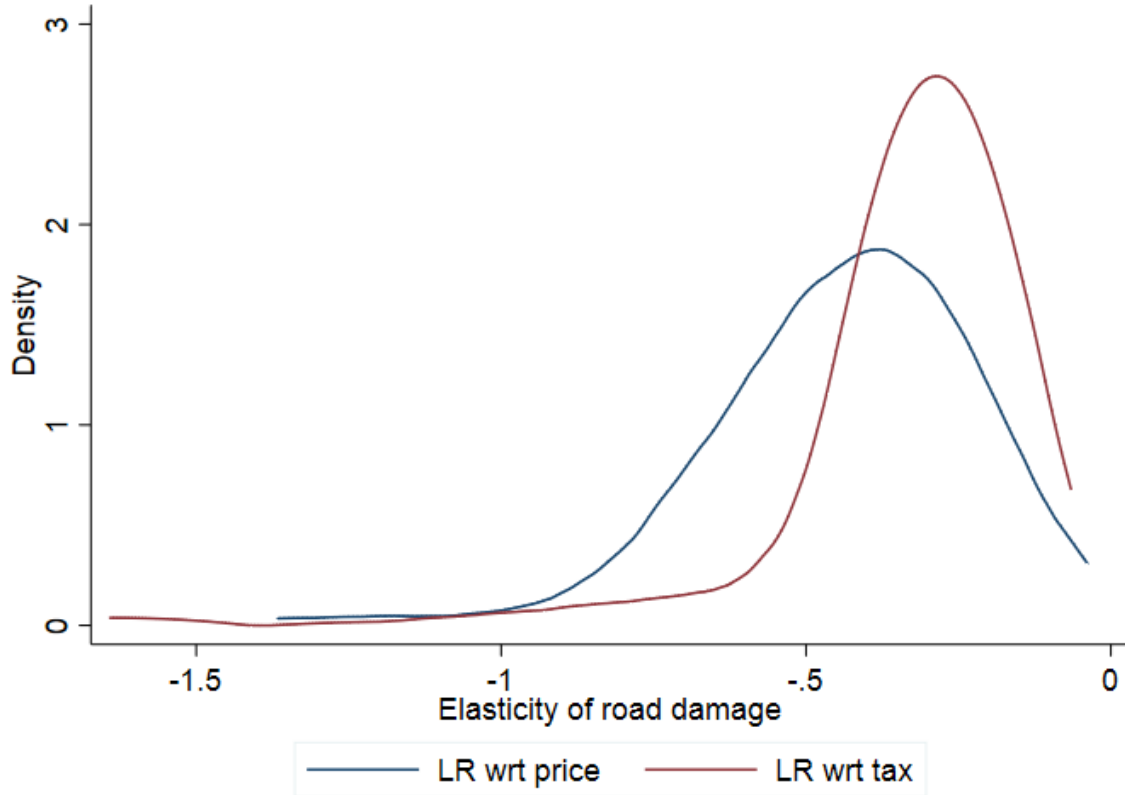


Figure 7.8: Country-specific road damage elasticities, graphical overview

Table 7.12 summarizes the key characteristics of the distributions shown in Figure 7.8.

Table 7.12: Country-specific road damage elasticities, numerical overview

Road damage	Long-run	
	wrt price	wrt tax
Default elasticity	-0.269	-0.497
Mean	-0.440	-0.335
Median	-0.415	-0.284

Road damage	Long-run	
5th percentile	-0.768	-0.699
95th percentile	-0.187	-0.173
Number of estimates	170	178

7.6.4 Vehicle-km travelled (VKT)

We analyze the effect of fuel prices on VKT in order to illustrate one of the main channels through which fuel prices affect congestion, accidents and road damage. We do not consider VKT a policy outcome per se and the effect of fuel prices on the other outcomes is calculated directly (not via the VKT elasticities).

7.6.4.1 Short-run elasticity

The estimated short-run elasticities of VKT wrt fuel price are shown Table 7.13. The short-run elasticity is estimated at -0.395, which is similar to the more elastic estimates in the literature (Table 7.1).

Table 7.13: Regression results short-run VKT

VKT	(1)	(2)	(3)	(4)	(5)	(6)
	pooled within OLS estimator					
Ln of gasoline pump price (2018 PPP-adj USD cents/liter)	-	-	-	-	-	-
	0.206***	0.0940	0.0523	0.395***	0.395***	0.476***
	(0.0276)	(0.0378)	(0.0239)	(0.0807)	(0.0805)	(0.015e-15)
Interaction lnsuper w/ Ln of number of vehicles per capita			0.631***			-
			(0.00195)			0.569***
						(8.36e-07)
Interaction lnsuper w/ Ln of population			0.0230			-
			(0.905)			0.0117
						(0.904)
Interaction lnsuper w/ Infant mortality rate (per 1,000 live births)			0.509**			-
						0.676***

VKT	(1)	(2)	(3)	(4)	(5)	(6)
			(0.0117)			(5.36e-08)
Interaction lnsuper w/ Number of motorcycles per capita			0.194			0.231***
			(0.205)			(0.00485)
Interaction lnsuper w/ Maximum speed on urban roads (in km/h)			0.199			-
			(0.136)			0.127*
			(0.0790)			
Covariates	No	Yes	Yes	No	Yes	Yes
Fixed effects	No	No	No	Yes	Yes	Yes
Interaction terms	No	No	Yes	No	No	Yes
Number of country_iso3_num				118	106	106
Robust pval in parentheses	0	0	0	0	0	0
Number of country FE	0	0	0	0	0	0

Robust p-values in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Ln(gasoline) is the natural logarithm of the gasoline pump price (2018 PPP-adjusted USD cents/liter). The parameter marked in green is the default short-run elasticity in CPAT for countries that have not sufficient data for country-specific elasticity estimation. Sample averages are subtracted from the interaction variables prior to interacting with the fuel price.

7.6.4.2 Long-run elasticity

The long-run estimate for the VKT elasticity is shown in Table 7.14. With an estimate of 0.228, our result is at the more inelastic side of estimates in the literature (Table 7.1).

Table 7.14: Regression results long-run VKT

VKT	(1)	(2)	(3)
			between
			es-
			ti-
			ma-
			tor
Ln of gasoline pump price (2018 PPP-adj USD cents/liter)	-	-	0.694
			0.493
			0.228
			(0.242)
			(0.652)
			(0.503)
Interaction lnsuper w/ Number of motorcycles per capita			0.131
			(0.824)

VKT	(1)	(2)	(3)
Interaction lnsuper w/ Population density (people per sq. km of land area)			5.058 (0.333)
Interaction lnsuper w/ Rule of law (from -2.5=low to 2.5=high)			0.222 (0.646)
Interaction lnsuper w/ Total length of road network (in km)			0.197 (0.436)
Interaction lnsuper w/ Maximum speed on rural roads (in km/h)			0.0638 (0.895)
Covariates	No	Yes	Yes
Interaction terms	No	No	Yes
Number of country_iso3_num	118	106	106
Robust pval in parentheses	0	0	0
Number of country FE	0	0	0

*Robust p-values in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Ln(gasoline) is the natural logarithm of the gasoline pump price (2018 PPP-adjusted USD cents/liter). The parameter marked in green is the default long-run elasticity in CPAT for countries that have not sufficient data for country-specific elasticity estimation. Sample averages are subtracted from the interaction variables prior to interacting with the fuel price.*

7.6.4.3 Country-specific elasticities

Similar to the other variables, Table 7.15 shows the variables selected by the algorithm for estimating the country-specific elasticities. We see that the road network (total length of the network, road density), the fleet (motorcycles, number of vehicles) and more general country characteristics (population size and density, infant mortality rate, GDP) enter into the calculation.

Table 7.15: Variables selected for country-specific VKT elasticity estimation

Short run	Long run		
wrt price	wrt tax	wrt price	wrt tax
Ln of number of vehicles per capita	Number of vehicles per capita	Total length of road network (in km)	Total length of road network (in km)

Short run	Long run		
Number of motorcycles per capita	Number of motorcycles per capita	Maximum speed on rural roads (in km/h)	Maximum speed on rural roads (in km/h)
Ln of population	Population density (people per sq. km of land area)	Number of motorcycles per capita	Number of motorcycles per capita
Infant mortality rate (per 1,000 live births)	Road density (in km per km ²)	Rule of law (from -2.5=low to 2.5=high)	GDP per capita (in 2018 PPP-adj USD)
Maximum speed on urban roads (in km/h)	Precipitation (in mm)	Population density (people per sq. km of land area)	Road density (in km per km ²)

Notes: The covariates used for estimating the country-specific elasticities are chosen by a data-driven machine learning algorithm among a list of 30 candidate variables.

The distribution of the resulting country-specific elasticity estimates is described in Figure 7.9 and Table 7.16. In the majority of countries, VKT is more elastic in the long-run than in the short-run.

Table 7.16: Country-specific VKT elasticities, numerical overview

VKT	Short-run		Long-run	
	wrt price	wrt tax	wrt price	wrt tax
Default elasticity	-0.395	-0.218	-0.228	-0.225
Mean	-0.282	-0.209	-0.561	-0.566
Median	-0.241	-0.220	-0.591	-0.620
5th percentile	-0.512	-0.245	-0.724	-0.891
95th percentile	-0.138	-0.128	-0.245	-0.126
Number of estimates	163	167	158	141

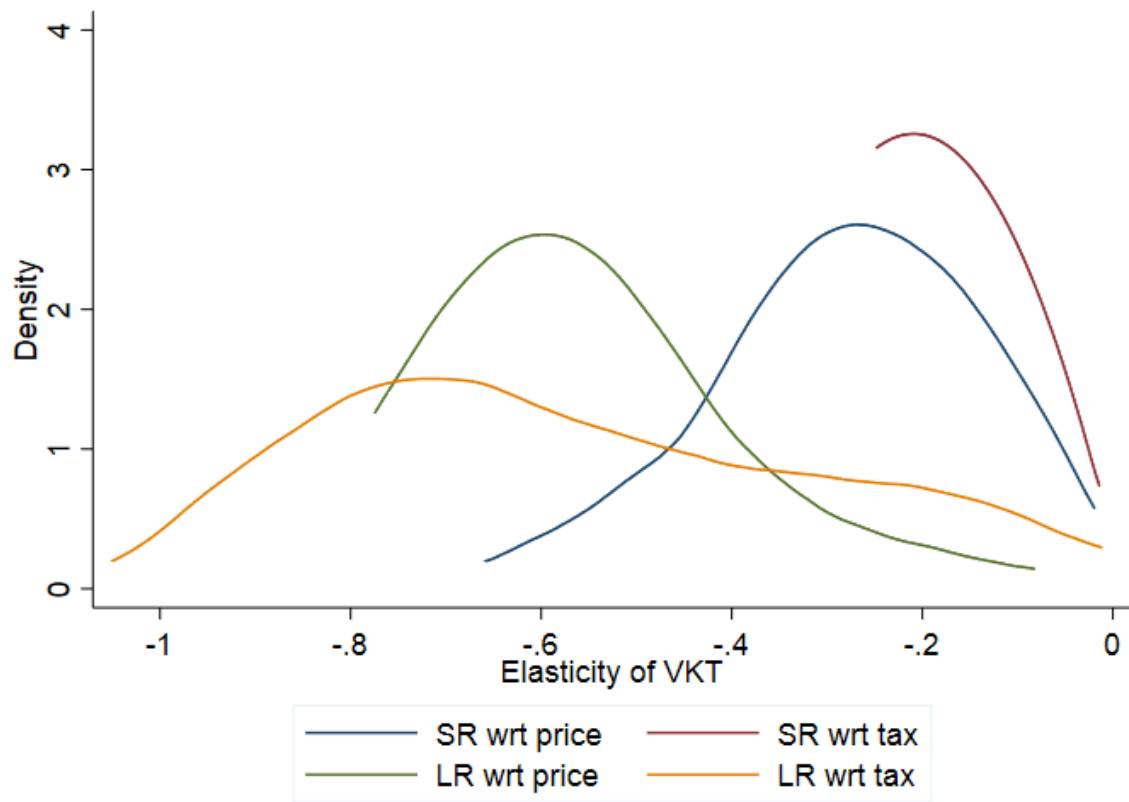


Figure 7.9: Country-specific VKT elasticities, graphical overview

7.7 Excel implementation: CPAT's Road Transport Module

7.7.1 General

The Road Transport Module takes as an input the road fuel price changes induced by the policy indicated by the user in the dashboard. The module then computes changes in VKT, congestion, accidents and road damage and presents them graphically in the dashboard tab. The information flow is schematized in Figure 7.10. Although the effect on VKT is computed, the other outcomes are modeled directly as a function of price, in order to avoid having to take functional form assumptions on the influence of VKT and its interaction with the other channels.

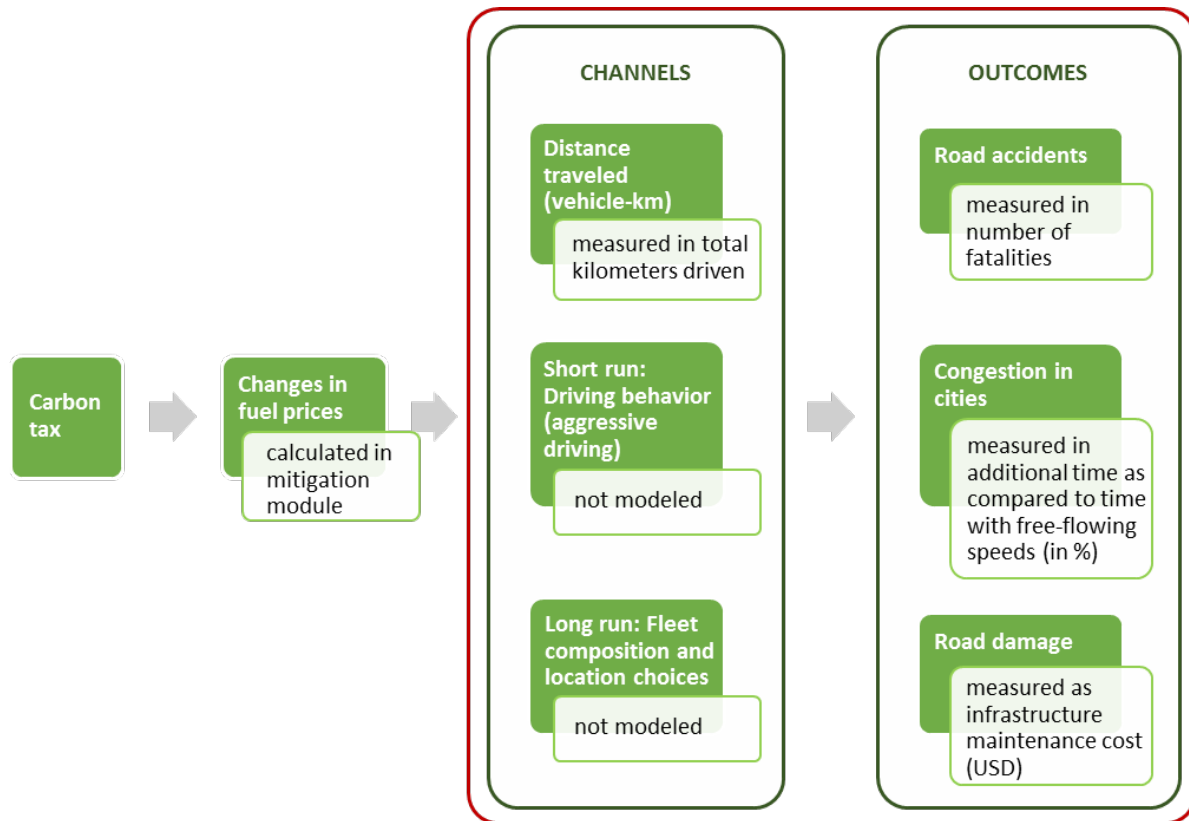


Figure 7.10: Input and output of CPAT's Road Transport Module

Note: Channels are shown to illustrate the economic theory; they are not modeled/estimated separately within CPAT. The estimated elasticities result of the interaction of all channels in the data.

7.7.2 Baseline forecasts

In order to graphically represent changes induced by the policy compared to a baseline, we must first establish a baseline forecast. The methodology in CPAT is identical for all three outcomes and VKT. It follows the following structure:

- Establish a linear forecast based on the average growth rate of available (often incomplete) time series of the variable in the past;
 - The sheet “Tran_Data” contains recent values of the outcome variables as well as the geometric average of growth rates over the past years.
- Adjust the variable’s linear forecast:
 - for (forecasted) future deviations from (observed) average past GDP growth using the estimated elasticity of the outcome wrt GDP,
 - for (forecasted) future deviations from (observed) average past population growth using the estimated elasticity of the outcome wrt population.

$$Y_t^{\text{baseline}} = \left(\frac{\text{GDP}_t}{\text{GDP}_{t-1}} - \overline{g^{\text{GDP}}} \right)^{\eta_{\text{GDP}}} \left(\frac{\text{pop}_t}{\text{pop}_{t-1}} - \overline{g^{\text{pop}}} \right)^{\eta_{\text{pop}}} Y_t^{\text{simple}} \quad (7.8)$$

where:

- Y_t^{baseline} is the baseline (without policy) forecast of variable Y ,
- Y_t^{simple} is the “naïve” linear forecast based only on past observed values of Y ,
- GDP_t and GDP_{t-1} are the contemporary and previous GDP (GDP growth forecast for coming years from IMF World Economic Outlook),
- $\overline{g^{\text{GDP}}}$ is the expected GDP growth (geometric average growth over past years),
- η_{GDP} is the elasticity of the outcome wrt GDP,
- pop_t and pop_{t-1} are the contemporary and previous population sizes (WB Population Estimates and Projections),
- $\overline{g^{\text{pop}}}$ is the expected population growth (geometric average growth over past years),
- and η_{pop} is the elasticity of the outcome wrt population size.

We need to subtract expected GDP/population growth from the actual (forecasted) GDP/population growth, as the past growth rates are implicitly included in the linear forecast Y_t^f .

Adjusting for GDP growth in this way should allow us to account for booms and recessions, as for example the graphically impressive drop caused by Covid-19.

7.7.3 Policy forecast

The impact of the carbon policy depends on the change in fuel prices and the variable's elasticity wrt fuel prices/taxes.

The fuel price is computed as follows:

- the baseline road fuel price is computed as the weighted average of baseline gasoline and diesel price, where the weights equal the respective fuel's share of baseline total road fuel consumption;
- the policy road fuel price is computed as the weighted average of policy gasoline and diesel price, where the weights equal the respective fuel's share of policy total road fuel consumption;
- the price change is defined as the ratio of the policy road fuel price over the baseline road fuel price.

We obtain the policy forecast Y_t^{policy} by weighting the price change by the elasticity wrt fuel price η_p .

$$Y_t^{\text{policy}} = \left(\frac{p^{\text{policy}}}{p^{\text{baseline}}} \right)^{\eta_p} Y_t^{\text{baseline}} \quad (7.9)$$

where p^{baseline} is the baseline road fuel price and p^{policy} is the policy road fuel price.

7.7.4 Dashboard graphics

For VKT and the three outcomes of interest, we establish similar graphics in the CPAT dashboard.

For each variable, there is a line graph representing the time series of the baseline forecast Y_t^{baseline} and the policy forecast Y_t^{policy} . An example is given in Figure Figure 7.11.

Source: Tomtom, own computations.

We then plot a bar chart of the difference between the two lines of Figure Figure 7.11, representing only the change induced by the policy. An example is given in Figure 7.12.

Source: WRS, OECD, UNECE, own computations.

Finally, we provide some general evidence of the effect of fuel prices on accident and congestion with a scatter graph. For this scatter graph, we combine cross-sectional country-level information for a given year with year-level information of all available years for the country for which the policy introduction is studied. We also add a linear trendline, which captures the negative correlation between fuel prices and our outcomes. An example is given in Figure 7.13.

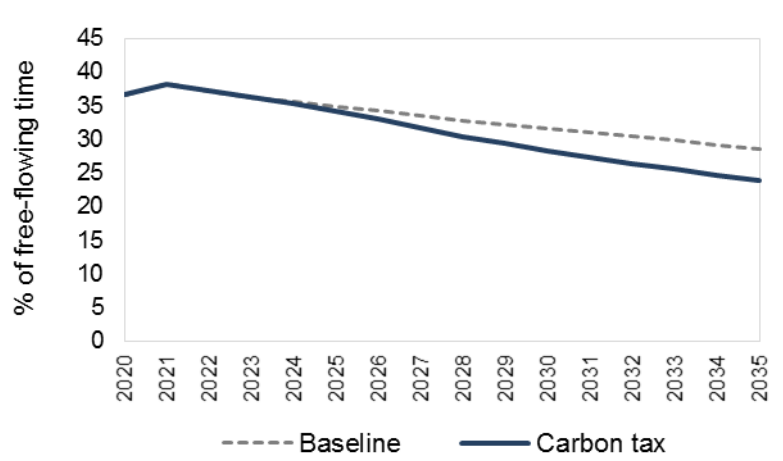


Figure 7.11: Urban congestion (additional time needed because of congestion, for US\$50 per tCO₂e in 2030), Mexico

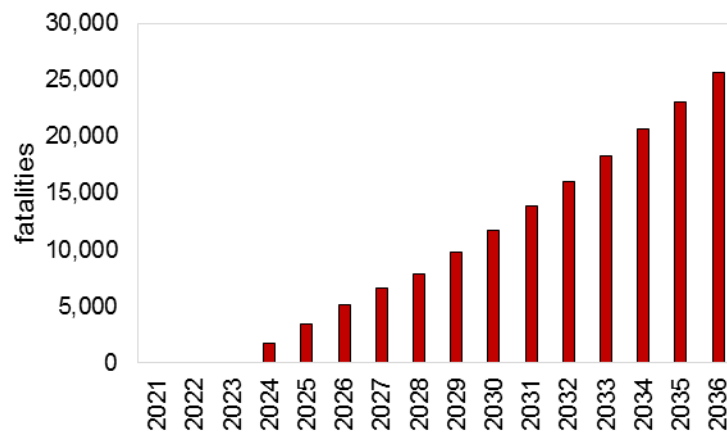


Figure 7.12: Averted deaths from road accidents (for US\$50 per tCO₂e in 2030), India

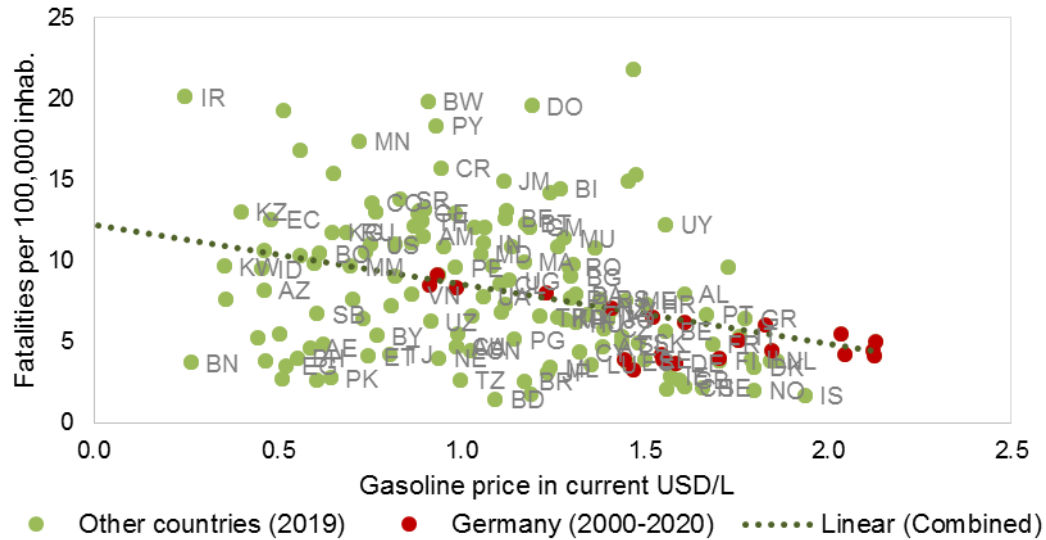


Figure 7.13: Historical relationship between fuel prices and road accident fatalities, global and Germany

Source: WRS, Enerdata, EIU, IEA, own computations.

7.7.5 Externality cost per liter of motor fuel

This section explains how CPAT computes the externality cost (per liter of motor fuel) from accidents and congestion. The externality costs are computed as the co-benefits from a carbon tax-induced reduction in motor fuel consumption.

The main road transport co-benefits of a carbon tax are a reduction in road accidents (from a reduction in driving, changes in the vehicle fleet, less aggressive driving, etc.) and a reduction in congestion (from a reduction in driving, an increase in car sharing, changes in the vehicle fleet, changes in transport timing decisions, etc.).

Within CPAT, the magnitude of these co-benefits is computed using empirical elasticities from a large historical dataset using econometric panel methods. Given the multitude of channels involved in the final result, the effect on accidents/congestion is not directly proportional to the change in vehicle-kilometers traveled (VKT) or the change in fuel consumption. For more details on the data and estimation procedure, please refer to the Technical Appendix to the CPAT Road Transport Module.

The externality cost is computed as follows:

- Compute baseline forecast of accidents/congestion *without policy*;

- Baseline forecasts take into account historical growth rates, adjusted for forecasted GDP and population growth.
- Compute policy forecast of accidents/congestion *with carbon tax* of users choice;
 - Policy forecasts are the baseline forecast adjusted for the fuel price change using the country-specific elasticity; this country-specific elasticity is empirically estimated and measures overall (i.e. across channels) which fuel prices affect accidents/congestion.
- Compute for policy and baseline scenarios the *monetary* value of accidents (multiplying fatalities by value of statistical life) and congestion (multiplying time lost in traffic times value of travel time);
- Compute the *change* in value of accidents/congestion;
- *Divide* change in value by change in motor fuel consumption from CPAT Mitigation Module.

The externality cost estimate varies each year. For simplicity, only one year is shown as an example in the CPAT Dashboard. As an example Figure 7.14 shows the graph for Colombia.

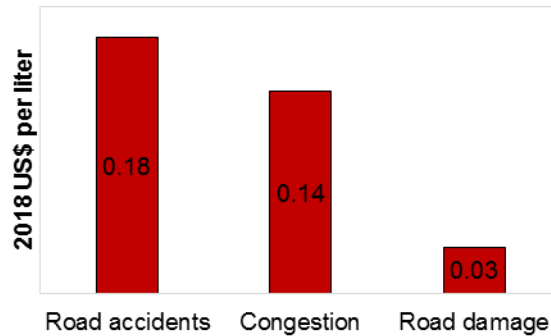


Figure 7.14: Externality cost per liter of motor fuel in 2024, Colombia

Source: Tomtom, WRS, UNECE, OECD, IMF, own computations.

Note that the TomTom Traffic Index is defined on the city-level. Therefore, the congestion externality shown in CPAT applies only the urban part of transport. To our knowledge, there is no database measuring congestion levels on the national level. Rural transport is assumed to be free of congestion, i.e. causing zero congestion externality cost.

7.8 Caveats

The CPAT Road Transport Module chooses a reduced-form econometric approach to predict the impact of carbon taxes on road transport externalities. Certain caveats must be kept in mind:

- The quality of the estimates relies on the quality of available data. For certain countries/years, there is no sufficient data to estimate country-specific transport externality elasticities. In these cases, an internationally estimated default value was used. In the Road Transport Module (Transport tab, section B – elasticities), the user can see whether country-specific or default elasticities have been used.
- Reduced-form approaches do not explicitly model the mechanisms. A carbon tax impacts transport demand through various channels: more fuel-efficient use of existing vehicles (e.g. speed, carpooling), switch to less carbon-intensive means of transport (e.g. public transport, non-motorized), reduction in the number/length of trips. The CPAT Road Transport Module cannot disentangle these channels, and can thus not attribute changes in outcomes to individual channels. In particular, carbon taxes make the use of private vehicles more expensive and CPAT cannot measure the loss from the value of non-realized trips.
- General equilibrium effects are not included, such as changes in prices or availability of the outside options. One example frequently discussed are electric vehicles (EVs). Currently, CPAT Road Transport Module does not include EVs. However, an extension of the CPAT Road Transport Module is planned in order to include EVs.
- Elasticities, such as estimated with the CPAT Road Transport Module’s methodology, predict the reaction of outcomes to *small* changes in carbon taxes. CPAT Road Transport module does not account for potentially non-linear responses to large policy changes. In particular, large policy changes across the world may induce technology changes and relevant changes in the vehicle fleet.
- A uniform carbon tax would impact not only private vehicles but also lower-emitting transport modes such as buses. An increase in the price of public transit could have a negative impact on people’s ability to reach jobs and essential services thereby contributing to fragmented labor markets and loss of welfare. Since low-income households are more likely to reduce their number of trips (instead of switching means of transport), a carbon tax could reduce their access to economic opportunities and thereby impact inequality. While it is not within the scope of CPAT1.0, understanding the potential impact of carbon pricing on access to employment is important to inform the development of more targeted policies that can offset any such negative distributional effects of a carbon tax on transit accessibility.

7.9 Status of upgrades since the last review, changes not implemented and remaining issues

We constantly update the dataset used to estimate the parameters behind the CPAT Road Transport Module. So far, CPAT reflects the last complete update using the WRS 2020 edition. A further update using the WRS 2021 edition is in progress.

As we are using proprietary data, we had to transform all non-shareable (proprietary) data into a shareable form. For the Road Transport Module, this was mainly achieved by using (near-future) forecast based on historic data forecasts, instead of the historic data itself.

We have further added estimates of the externality cost per liter of motor fuel, described in Section 7.7.5.

We are still working on two features not yet implemented:

- *Integration of electric vehicles (EVs)*: The introduction of EVs and their necessary charging infrastructure is relatively slow, especially in developing countries. So far, we have struggled to get sufficient data for credible estimations. Nevertheless, we are aware that EVs may fundamentally change the link between traffic (including accidents and congestion) and carbon taxes. We are thus working on a methodology to include EVs and EV-supporting policies into CPAT.
- *Between-module consistency*: Currently, the VKT estimates in the CPAT Road Transport Module are not linked to the transport CO₂ in the Mitigation Module. In fact, VKT and CO₂ may follow distinct paths as technology and driving habits (e.g. number of people in a vehicle) change. Nevertheless, future versions of CPAT will improve the coordination between modules.

7.10 Appendices

7.10.1 Detailed variable list with data sources

Definition	Source	Interpolated
Outcomes	Total road distance travelled (in million vehicle-km)	WRS, OECD ¹⁴

¹⁴If several sources are indicated, the order is respected: only missing observations of the first source are completed using the second source, and so forth.

Definition	Source	Inter- polated
	Number of fatalities by road accident: Any person killed immediately or dying within 30 days as a result of an accident (accident involving at least one road vehicle in motion), excluding suicides	WRS, UN- ECE, OECD
	Congestion index (in % deviation from free-flowing speed)	TomTom
	Road maintenance cost (in million 2010 USD)	WRS
Covariates	Year	
	Retail price per liter of motor gasoline (unleaded Octan 95) at the pump (in 2010 USD cent/liter)	IMF, Ener- data, IEA, GIZ
	Retail price per liter of motor diesel at the pump (in 2010 USD cent/liter)	IMF, Ener- data, IEA, GIZ
	Population	WDI X
	GDP per capita (in 2010 USD)	WDI
	Youth share (population 15 to 24 years-old in % of total)	WDI
	Alcohol, recorded per capita (15+) consumption (in liters of pure alcohol)	WHO/GHO
	Maximum speed in rural areas ¹⁵ (in km/h)	WHO/GHO
	Maximum speed in urban areas (in km/h)	WHO/GHO
	Control of corruption (from -2.5=low to 2.5=high)	WGI
	Road density (km of road per km ² of country area)	WRS
	Share of motorcycles (in % of total vehicle fleet)	WRS X
	Vehicles per capita	WRS X
Additional candidate variables for elasticity		
	Yearly in rainfall (in total mm)	CCKP
	Annual number of days with minimum temperature 0°F/-17.8°C	NCEI
	Annual number of days with minimum temperature 32°F/0°C	NCEI

¹⁵All variables from the WHO Road Safety reports/Global Health Observatory are only available for 2011 and 2017

Definition	Source	Inter-polated
	Annual number of days with minimum temperature 90°F/32.2°C	NCEI
	Extreme minimum temperature for the year (in °C)	NCEI
	Satisfaction with public transport (in %)	SDR
	GDP (in 2010 USD)	WDI
	Infant mortality rate (per 1,000 live births)	WDI
	Population density (in persons/km2)	WDI X
	Share of urban population (in % of total population)	WDI X
	Rule of law (from -2.5=low to 2.5=high)	WGI
	Blood alcohol concentration (BAC) legal driving limit (in g/dl)	WHO/GHO
	Maximum speed (average of urban and rural, in km/h)	WHO/GHO
	Seat belt wearing rate in front seat (in %)	WHO/GHO
	Motorcycles per capita	WRS X
	Number of lorries and trucks	WRS X
	Share of lorries and trucks (in % of total vehicle fleet)	WRS X
	Share of paved roads (in % of total road km)	WRS X
	Total length of road network (in km)	WRS X

7.10.2 Countries/years covered by the dataset

no outcomes	None of the outcomes
some outcomes and covars	Some outcomes and covariates
all outcomes, but not all covars	All outcome variables, but not all covariates
all	All outcomes and all covariates

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	
Afghanistan	no	no	no	some	some	some	some	some	some	some	some	some	some	some	some	some	some	some	some	some	some	some	some	some	some	some	some	no
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	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars	vars

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