OECD Economics Department Working Papers No. 1749

Options for assessing and comparing climate change mitigation policies across countries

Mauro Pisu,

Filippo Maria D'Arcangelo,

Assia Elgouacem,

Tobias Kruse,

Yannick Hemmerlé

https://dx.doi.org/10.1787/b136e575-en

OECD

Organisation for Economic Co-operation and Development

ECO/WKP(2023)2

Unclassified **English - Or. English**

23 February 2023

ECONOMICS DEPARTMENT

OPTIONS FOR ASSESSING AND COMPARING CLIMATE CHANGE MITIGATION POLICIES ACROSS COUNTRIES

ECONOMICS DEPARTMENT WORKING PAPERS No. 1749

By Mauro Pisu, Filippo Maria D'Arcangelo, Assia Elgouacem, Yannick Hemmerlé and Tobias Kruse

All Economics Department Working Papers are available at www.oecd.org/eco/workingpapers.

JT03512976

ABSTRACT/RÉSUMÉ

Options for assessing and comparing climate change mitigation policies across countries

This paper reviews different methods for assessing and comparing across countries the impact of climate change mitigation policies and policy packages on emissions. Broadening and deepening past and recent mitigation policies' stocktaking efforts, as well as mapping them to their emission base, is key to comparing pricing and non-pricing policies and feed comparable information to ex-post empirical and ex-ante analytical models. Ex-post empirical approaches can provide benchmark estimates of policies' effectiveness from past data and furnish key parameter estimates to calibrate ex-ante analytical models (partial equilibrium, general equilibrium and integrated assessment models). Moreover, they can complement ex-ante analytical models by empirically validating their assumptions and informing models' choices. Ex-ante analytical modelling are well suited to provide long-term forward-looking projections also on yet-to-be implemented policies. Sector specific models, such as energy system models, are well suited for a granular assessment of the impact on emissions of a wide range of price- and non-price-based policies. Outputs from the ex-ante sector-specific models can then feed into a Computable General Equilibrium model to quantify the effect of individual policies and policy packages on emissions, taking into account second order effects and reducing the risk of double counting the effect of policies.

JEL codes : Q54; Q58

Keywords: Climate change, stocktaking of mitigation policies, evaluation of mitigation policies, energy system models, general equilibrium models

****

Options pour évaluer et comparer les politiques d'atténuation du changement climatique entre les pays

Cette publication passe en revue différentes méthodes destinée à évaluer et comparer l'impact des politiques d'atténuation du changement climatique et l'ensemble des mesures sur les émissions entre les différents pays. Élargir et approfondir l''inventaire des efforts des politiques d'atténuation passées et récentes, ainsi que les cartographier à leur base d'émission, est essentiel pour comparer les politiques de tarification et de non-tarification et ainsi fournir des informations comparables aux modèles empiriques ex-post et aux modèles analytiques ex-ante. Les approches empiriques ex post peuvent fournir des estimations de référence sur l'efficacité des politiques à partir de données passées et fournir des estimations de paramètres clés pour calibrer les modèles analytiques ex ante (modèles d'équilibre partiel, d'équilibre général et d'évaluation intégrée). De plus, ils peuvent compléter les modèles analytiques ex ante en validant empiriquement leurs hypothèses et en éclairant les choix de modèles. La modélisation analytique ex ante est bien adaptée pour fournir des projections prospectives sur le long terme mais également sur les politiques qui doivent encore être mises en œuvre. Les modèles spécifiques à un secteur, tels que les modèles de systèmes énergétiques, sont bien adaptés à une évaluation granulaire de l'impact sur les émissions d'un grand nombre de politiques, basées et non basées sur les prix. Les résultats des modèles sectoriels ex ante peuvent ensuite alimenter un modèle d'équilibre général calculable destiné à quantifier l'effet des politiques individuelles et des ensembles de mesures sur les émissions, tout en tenant compte des effets de second ordre et en réduisant le risque de double comptage de l'effet des politiques.

JEL codes : Q54; Q58

Mots clés : Changement climatique, état des lieux des politiques d'atténuation, évaluation des politiques d'atténuation, modèles de systèmes énergétiques, modèles d'équilibre général

Table of contents

FIGURES

TABLES

Options for assessing and comparing climate change mitigation policies across countries

By Mauro Pisu, Filippo Maria D'Arcangelo, Assia Elgouacem, Yannick Hemmerlé and Tobias Kruse[1]

Introduction

The recent momentum to increase climate ambition is encouraging. In recent years, more than 130 countries have committed to ambitious emission reduction targets in the Nationally Determined Contributions (NDCs). A growing number of countries target achieving net-zero greenhouse gas emissions (GHG) by mid-century. How governments will meet such targets is to be determined by each country individually, consistent with the principles of the multilateral climate policy architecture as stipulated in the Paris Agreement. Every country has a different starting point and capabilities. It faces different national circumstances, which will determine its contribution to the Paris Agreement goal of limiting global warming to well below 2, preferably to 1.5 degrees Celsius, compared to pre-industrial levels.

However, despite progress made to date, policy actions and the pace of progress remain highly dissimilar across countries and, at the global level, largely insufficient. Depending on national circumstances, countries use or plan to use a widely different set of price-based and non-price-based policies to lower GHG emissions. Some countries price carbon emissions directly, through carbon taxes or emission trading systems (among G20 countries, 13 of them price carbon explicitly) (OECD, 2021[1]; IMF/OECD, 2022[2]), or indirectly, through other price-based instruments such as excise taxes on fossil fuels, carbon-differentiated motor vehicle taxes and subsidies (OECD, 2021[1]). Non-price-based instruments (e.g., energy efficiency standards, outright bans on specific products or activities, R&D subsidies and public investments) have become ubiquitous as countries deploy them alongside or instead of price-based instruments (IMF/OECD, 2022[2]).

---

[1] An earlier version was discussed at a meeting of Working Party No.1 (WP1) of the OECD Economic Policy Committee. The authors would like to thank Luiz de Mello, Alain de Serres, Douglas Sutherland, Boris Cournède, Volker Ziemann, Jean Chateau, Falilou Fall for their valuable comments. They would also like to thank Dirk Röttgers from the Centre for Tax Policy and Administration, for his continuous engagement with the paper, as well as Shardul Agrawala, Damien Dussaux, Elisa Lanzi, Rob Dellink from the Environment Directorate for comments on earlier versions of the paper; Rodrigo Pizarro, Daniel Nachtigall and Marcia Rocha from the Environment Directorate for valuable interaction related to the IFCMA; Miglé Petrauskaite for outstanding research assistance; Dacil Kurzweg and Sisse Nielsen for excellent editorial assistance.

This diversity of policy approaches is necessary to accommodate different national circumstances (D'Arcangelo et al., 2022[3]), but it hampers the assessment and comparison of mitigation strategies. The lack of comparable metrics to measure the effectiveness of policies in reducing emissions amplifies concerns over competitiveness losses and carbon leakage, undermining trust and raising the risks of implementation slippage and free riding.

Objective data and information on climate change mitigation policies and their effects on emissions is essential to support progress towards countries' emission-reduction targets while helping to limit adverse interactions with trade and development agendas. This, in turn, can inform and foster multilateral dialogue and build trust in other countries' progress towards emission targets.

This paper discusses available options and ongoing work to assess and compare climate change mitigation policies, illustrated by country examples. It contributes to the Inclusive Forum on Carbon Mitigation Approaches (IFCMA) (Box 1), which aims at improving the assessment and comparability of climate change mitigation policies across countries, and contributes in establishing its methodological foundations.

Box 1. The Inclusive Forum on Carbon Mitigation Approaches

The Inclusive Forum on Carbon Mitigation Approaches (hereafter IFCMA) was launched on 10 June 2022 under the leadership of the OECD. In part to support multilateral exchange, the IFCMA seeks to provide comprehensive analysis on policies to address climate change, their comparative effectiveness and costs. The goal is to foster a more ambitious, globally more coherent and better coordinated approach to carbon mitigation efforts. Despite significant international efforts, there is, at present, no single international forum providing such comprehensive analysis.

The IFCMA will take stock of the main price-based and non-price-based climate change mitigation policies and policies highly relevant to climate change mitigation and develop tools to improve the comparability of these policies, primarily in terms of their effectiveness in reducing greenhouse gas emissions.

The IFCMA presently comprises of two modules. The objective of Module 1 is to produce a database of IFCMA countries' principal climate change mitigation and climate change mitigation-relevant policies, and to map policies to the emissions that they apply to, to the extent possible. Climate change mitigation –relevant policies are those policies that significantly affect greenhouse-gas emissions but whose main stated policy goal is not climate change mitigation. The sector scope and the coverage of climate change mitigation-relevant policies would be limited at first and broadened gradually over time. The focus of Module 2 will be on estimating policy effectiveness in terms of the greenhouse gas emission reductions that individual policies or policy packages covered by the work in Module 1 are expected to achieve and on exploring methodologies for measuring carbon intensity of goods or sectors. Both modules will be undertaken in consultation with country experts government officials and, as needed, other experts.

The paper starts by discussing general considerations with a bearing on the assessment of the effectiveness of policies in terms of emission reductions. These include what emissions and jurisdictions to cover, how to deal with overlapping policies and how to establish baselines. A more comprehensive stocktaking of policies than what is available to date would allow for documenting the diversity of policy approaches across countries and providing valuable information to inform policy discussions. It would also provide crucial information for the assessment and comparison of the impact of a large set of policies or policy packages on emissions. Mapping policies to their emission bases would complement the stocktaking by identifying what emission sources policies apply to (i.e. what emissions policies cover).

This paper then reviews options for assessing the impact of policies on emissions. It categorises them into two broad groups: the ex-ante analytical approach and the ex-post empirical approach. The former provides insights into the potential future effects of current or planned policies based on economic theory and a country's economic structure. The latter employs statistical and econometric methods to link emission reductions to policies based on past implementations. Ex-post empirical approaches can complement ex-ante analytical techniques. For example, empirically derived emission reduction elasticities can help to calibrate ex-ante analytical models using country- and sector-specific data, in addition to validating assumptions of ex-ante analytical models.

The paper's final section discusses possible next steps and challenges, focusing on assessing policy effectiveness in terms of emission reductions. Practical ways forward need to consider the strengths and limitations of the chosen methods, their availability, the expertise necessary to operate them, in addition to resource constraints. The assessment of a large number of price-based and non-price-based climate change mitigation policies and their variety call for the use of detailed ex-ante sector-specific models first, such as energy system models, that provide a good compromise in terms of outcomes comparability and policies' granularity and scope. Outputs from the ex-ante sector-specific models could then feed into a CGE model to quantify the effect of individual policies and policy packages on emissions, taking into account second order effects and reducing the risk of double counting the effect of policies. Empirically derived emission reduction elasticities can help calibrate ex-ante analytical models and can help validate their assumptions.

General considerations

This section discusses some general issues relating to assessment of the effect of policies on emissions. These cover the type of emissions, the jurisdiction (i.e., supranational, national and subnational), how to deal with overlapping policies and how to choose a baseline. In addition, collecting detailed and comprehensive information on countries' climate change mitigation policies is a key step to assess and compare the impact of policies on emissions. Box 2 provides more information on ongoing OECD efforts in this area.

Box 2. Stocktaking and mapping mitigation policies

The OECD Centre for Tax Policy Analysis and Environment Directorates are developing a framework for collecting information on countries' principal climate change mitigation policies and, to the extent possible, how to map them to emissions. They also seek to include relevant policies, meaning those that significantly affect GHG emissions although their stated policy goal is not climate change mitigation. A detailed note presenting this framework will be discussed at the Joint Meeting of Tax and Environment Experts (JMTEE) in mid-November 2022.

Many current and past efforts provide basic information on policies or aggregate them to a level useful to different stakeholders. These include the Policy Instruments for the Environment (PINE) database developed by the Environment Directorate, the Policies and Measures (PaM) database of the European Environment Agency and the Climate Action Tracker developed by the New Climate Institute. However, the focus of these efforts rarely is on the full comparability of policies to inform policy discussions and even less on detailing the relation between the policies and GHG emissions.

The stocktaking of policies under development cover, within a coherent framework, a larger set of mitigation policies and sectors at a more granular level than has been done so far. The mapping of policies to their emissions bases will allow for identifying what emission sources policies apply to, i.e. which emissions policies cover.

The stocktake will cover both price-based and non-priced-based policies and build directly on existing OECD climate change mitigation policy work while also involving additional data collection. It will build on OECD's Taxing Energy Use and Effective Carbon Rates reports for price-based measures. Non-price-based measures will include regulatory and support policies that are relevant for mitigating the principal GHG emissions (carbon dioxide, methane, nitrous oxide, fluorinated gases).

The stocktake will be open-ended, i.e. there is no ex-ante limitation to scope, and continual updates and extensions are possible. A typology of policies and a methodology to classify the set of policies to be included in the analysis will guide the database's development and structuring. This typology of policies will be based on the literature and further developed through pilot studies for selected countries and sectors. The methodology and typology will be adapted as needed as the country and sector scope of the database are expanded.

The stocktake will rely on collaboration with country experts (government officials and, as needed, other experts) to ensure that coverage is sufficiently comprehensive, detailed and comparable across countries but at the same time manageable and not exceedingly large.

The stocktaking and mapping of climate policies is a prerequisite for assessing and comparing the impact of policies on emissions (discussed in the next section). However, the stocktaking and mapping of policies is a valuable exercise in itself as it could inform choices on how to adjust or add policies to increase emission coverage or enhance policy stringency. In addition, this exercise enables detailed documentation of the diversity of policy approaches across countries. Data and results of the stocktaking and mapping may also feed into future research, including at the OECD.

Source: Forthcoming scoping paper to be discussed at the JMTEE meeting in November 2022.

Deciding on which emissions to cover

The type of GHGs covered by the analysis will determine its scope, including its sectoral and policy coverage. Non-CO_2 GHGs such as methane[2], fluorinated gases[3] or nitrous oxide[4] are less abundant but, for the same weight or volume, have a higher global warming potential than CO_2 as they may remain longer in the atmosphere (their "lifetime" is longer) or absorb more radiant heat (their "radiative efficiency" is higher). For example, the impact of a molecule of methane on global warming is almost 30 times larger (over 100 years) than of a molecule of CO_2 as a result of its markedly higher radiative efficiency, which is only partly offset by its shorter lifespan (a decade against 300-1 000 years for CO_2). The global warming

[2] CH_4, produced from the agriculture sector or gas pipelines' leakages.

[3] F-gases, used in a wide range of products such as refrigerators, air conditioning, electronics, cosmetics, pharmaceutical products, high voltage switchgear and in the production of magnesium and aluminium

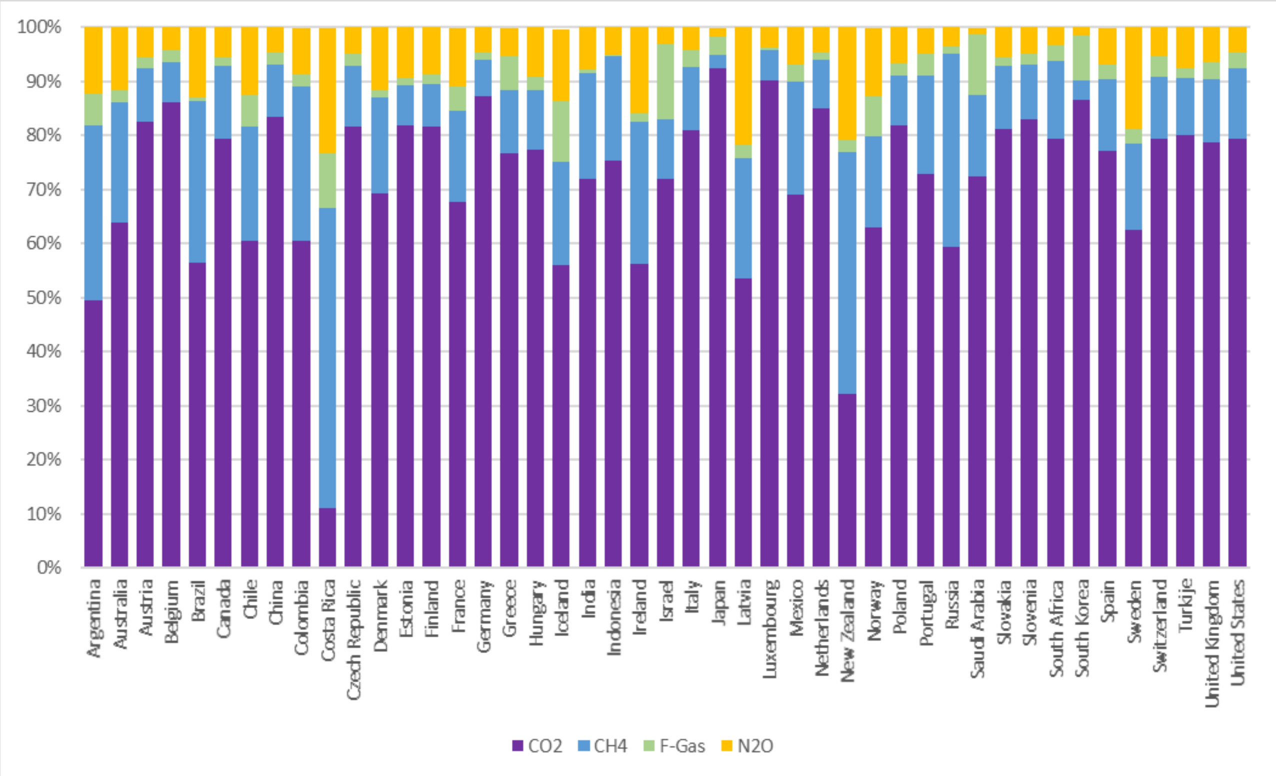
[4] N_2O, produced from various agricultural soil management activities, such as application of fertilisers, wastewater treatment, fuel combustion and some industrial process, such as the production of nylon and other synthetic products

potential (GWP) of nitrous oxide and some fluorinated gases is even higher than that of methane (US EPA, 2022[4]).

The composition of GHG emissions and their contribution to global warming varies across countries, depending on their industrial structure and, to a certain extent, policies (see Box 3 for examples from South Africa and the Netherlands). CO_2 accounts for most of the contribution to global warming in most countries, followed by methane and nitrous oxide. Notable exceptions include Costa Rica, New Zealand, Brazil, Chile, Colombia, Latvia, Iceland, Ireland and Sweden, featuring high contributions from methane and, less often, nitrous oxide (Figure 1).

Figure 1. Breakdown of greenhouse gas emissions by gas, 2019

Share of GHG in CO2 equivalent



Note: 2019 country-level greenhouse gas emissions data across all sectors (incl. LUCF), expressed in megatons of CO_2 equivalents (CO2e).
Source: World Resources Institute (2022[5])

Box 3. Tracking greenhouse gas emissions: examples from South Africa and the Netherlands

Countries have followed different approaches when targeting greenhouse gases, some tackling CO_2 emissions explicitly, while others are tackling a more comprehensive range of GHGs. The following examples from the Netherlands and South Africa illustrate this issue:

- South Africa is focusing on reducing several "priority pollutants"—carbon dioxide, methane, nitrous oxide, and fluorinated gases. Carbon dioxide accounts for about 80% of South Africa's total GHG emissions expressed in CO_2 equivalent (CO_2e) (Figure 1). Across sectors, fossil fuel intensive ones (such as power generation) are by far the largest emitter of carbon dioxide, agriculture and waste management of methane, while nitrous oxide comes primarily from agriculture and energy sectors. The carbon tax that came into effect in 2019 measures CO_2e of these gases and covers 41% of CO_2 emissions from energy use (OECD, 2021[6]; DFFE, 2021[7]).

- The Netherlands monitors the impact of its policies on greenhouse gas emissions through an emissions inventory system, which estimates and reports emissions by sources and removals by sinks on an annual basis. The bulk of total GHG emissions comes from carbon dioxide (around 85% of CO_2e). Nitrous oxide and methane arising from agriculture remain important in the Dutch context (accounting for most of the remaining 15% of CO_2e emissions). The agricultural sector remains the country's largest contributor to methane emissions, accounting for almost 70% of them (RIVM, 2021[8]).

Tracking policies and evaluating their impact on all GHG emissions can be difficult as cross-country data on non-CO_2 GHGs are less comprehensively available and can be uncertain to different degrees. The latest IPCC report (Chapter 2) (Parmesan et al., 2022[9]) evaluates these uncertainties to ±8% for CO_2 from fossil fuel and industrial processes, ±30% for methane and F-gases, ±60% for nitrous oxide and ±70% for CO_2 from land use, land-use change, and forestry (LULUCF). GHG comparison metrics, such as the GWP, bring about their own uncertainties, making the assessment of the contribution of different GHGs to rising temperature more difficult. The urgency of tackling global warming and the different shares across countries of GHGs in terms of CO_2 equivalents (CO_2e) call for tracking all GHGs. This can allow governments to focus efforts on reducing first those GHGs with the largest contribution to global warming and low abatement costs. For instance, tracking methane emissions with satellite images is allowing companies to identify leakages in gas pipelines and repair them, which is often cost-effective.

Deciding on which jurisdictions to cover

Climate policies across different levels of jurisdictions (i.e. supranational, national and sub-national levels) may overlap, creating synergies or trade-offs. European Union (EU) policies, such as the EU's emission trading system for emissions (EU ETS), are a case in point as they may interact with national policies in complex ways. Indeed, the EU ETS fixes the total amount of emission permits. As a result, stricter national regulation may reduce emissions in some countries, thereby freeing up area-wide emission permits and lowering their prices. Lower permit prices allow other countries to raise their GHG emissions, thus offsetting the effect of stricter regulation in other countries (i.e. the so-called "waterbed effect").

Many countries implement policies to lower GHG emissions at both national and sub-national levels (de Mello and Martinez-Vazquez, 2022[10]). These policies might have similar aims and overlap, complicating the assessment of the effect of individual policies. On the one hand, focusing only on national policy instruments may give a partial picture of climate policies in countries whose sub-national governments have responsibilities over climate change and other policy areas affecting emissions (e.g., transport and energy infrastructure). On the other hand, including all relevant policy instruments across sub-national jurisdictions (e.g. the 50 US States) would significantly widen the scope of the exercise, making it substantially more resource intensive.

Countries vary widely in how different levels of government interact with respect to climate change policies (see Annex A). In the United States, for instance, states and counties are responsible for a wide range of climate related policies. In India, in contrast, the federal government has relatively strong fiscal powers and bureaucratic capabilities compared to the states and has been primarily responsible for setting the agenda and policies on climate change issues. Canada lies between the cases of the United States and India as provinces and territories are responsible for most climate change policies, but the federal government plays a vital role in setting minimum standards, oversight and coordination. Annex A outlines the division of responsibilities between national and sub-national governments in Germany and South Africa.

Covering and assessing the effects of all polices across all sub-national jurisdictions would be desirable, but it is likely to involve substantial resources and is unlikely to be unfeasible. Choices need to be made based on the size of sub-national governments and expected impact of policies on emissions. For example, tracking California polices may be justified by the size of its economy and emissions and relevance of its policies for other states. Similarly to the sectoral coverage, sub-national policies could be added gradually to the policy-scope.

Deciding on the treatment of overlapping policy instruments

Countries often implement a combination of policies to cut emissions from the same source. A country might decide to tax high-emission products, label them, and launch an information campaign on the relevance of these labels. The tax and the information campaign could increase consumers' awareness of the need to label emission-intensive products, while the labels help consumers to select low-emission alternatives (OECD, 2022[11]). Informed by empirical policy evaluations, the share of emission reductions arising from the tax, the labelling and the information campaign could be allocated to different policies. Indeed, carbon taxes and emission trading schemes can be particularly effective in reducing emissions (Andersson, 2019[12]; Dechezleprêtre, Nachtigall and Venmans, 2018[13]; Abrell, Kosch and Rausch, 2022[14]). However, the causal impact of labelling or information campaigns can be more difficult to estimate and may be smaller (Lohmann et al., 2022[15]; Cohen and Vanderbergh, 2012[16]; Andor, Gerster and Peters, 2022[17]). If allocating emission reductions to different overlapping policies is not feasible, one could focus on the total effect of overlapping policies.

In practice, countries and international organisations use various methods to compute the effects of overlapping policies. The Intergovernmental Panel on Climate Change (IPCC) AR6 report (IPCC, 2022[18]), for instance, illustrates one potential approach to correct the overlap arising between the electricity supply and the electricity demand sectors. If the electricity sector is extensively decarbonised, the avoided emissions due to measures aiming at raising energy efficiency and electricity production from renewable sources will be significantly lower. To take this into account, the report takes only 25% of the estimated total emission reduction arising from energy efficiency measures. Annex A provides additional examples from the Netherlands and South Africa.

One possibility would involve accounting for such policy overlaps on a case-by-case basis while following a common methodology (yet to be developed) to ensure comparability across countries.

Establishing a baseline against which to compare future GHG emissions

The impact of policies on emissions needs to be measured against a baseline showing the evolution of GHG emissions in the absence of mitigation policies. Selecting a baseline scenario involves making choices about the set of policy instruments to be included in the baseline and about the time horizon of the analysis. The analysis could include, for example, policy measures introduced following the Kyoto Protocol in 1997 or the Paris Agreement in 2015. However, the "starting point" could differ across the countries covered. Some countries had already implemented numerous measures affecting GHG emissions years before these agreements, while others had done little to limit their emissions. Such a choice would exclude some of the most important policy measures affecting GHG emissions, in particular taxes on motor vehicles and fossil fuels, which were introduced for reasons unrelated to reducing emissions.

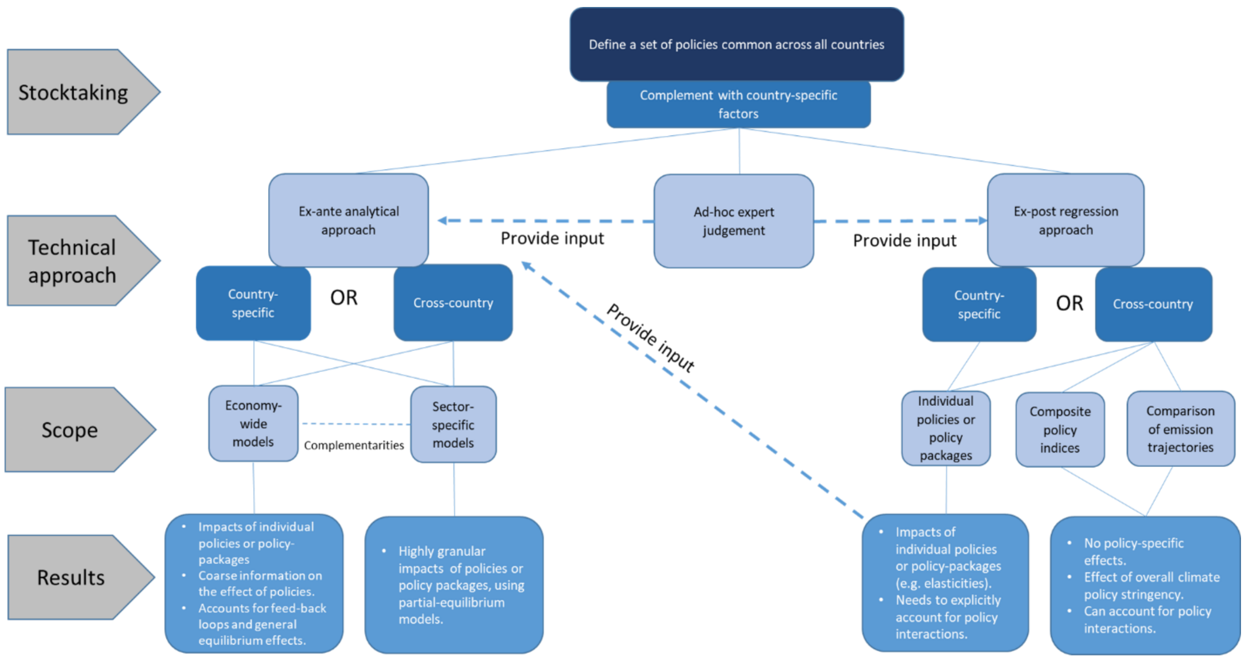
Another choice entails the time horizon over which to quantify the emission reductions of policies. The effect of some policies may materialise only several years following their introduction, as low-carbon alternatives are progressively developed and deployed and firms and households adjust their behaviour. The baseline builds on various assumptions concerning the evolution of key socio-economic variables, including GDP, population growth and energy intensity. The longer the time horizon of the projection period, the more likely the assumptions underlying the evolution of these key variables be violated as of various factors, such as technological developments and social changes. The recent and sudden disruption in energy markets caused by the war in Ukraine provides an example of the difficulties in building baselines robust to unexpected events. Baselines will need to update in light of such events.

Relying on multiple baselines would help to recognise the uncertainties of long-term projections. Baseline scenarios could vary based on their macroeconomic assumptions, including price developments of fossil fuels, GDP and population growth paths, and structural factors, such as the functioning of energy markets and the extent of fossil fuel import restrictions. Having different baseline scenarios could allow for exploring the impact of macroeconomic changes on policies' effectiveness in terms of emission reductions.

Assessing the effect of policies on emissions

Various technical approaches exist to compute and attribute emission reduction to policies, which yield different types of results (Figure 2). This paper distinguishes two main technical approaches to assess emission reductions: ex-ante analytical and ex-post regression approaches. Ex-ante analytical approaches provide insights into the potential effects of policies prior to their implementation based on economic theory (i.e., modelling the behaviour of firms, households and governments) and information on a country's economic structure. Ex-post regression approaches employ statistical and econometric methods to link emission reductions to policies that have already been implemented. The two approaches are complementary as the information collected for the latter can feed into the former. For instance, empirical estimates derived using the ex-post regression techniques (e.g. elasticities) can be used to calibrate ex-ante analytical models.

Figure 2. Approaches to assessing emission reductions from policy packages



Note: This figure shows different approaches to assess emission reductions from policies or policy packages.
Source: OECD.

Expert judgement can complement both ex-ante analytical and ex-post regression approaches. The impact of policies on emissions may depend on nuanced and detailed characteristics of the policy being studied (and of other policies with which it interacts) that ex-ante analytical and ex-post regression approaches may find it difficult to capture (Box 4).

Box 4. The role of expert judgement in evaluating climate policy-related emission reductions

Capturing all country, sectoral and technological specificities that contribute to the effectiveness of policies in reducing emissions may be challenging for both ex-ante analytical and ex-post regression approaches.

Experts need to thoroughly understand the country and some of its specific policies and sectors, the functioning of its energy markets, how different policy instruments interact, the typical behaviour of different market players, and the legal system. Expert judgement is needed to ensure the most suitable analytical representation and parameter choices and assess and interpret modelling results, and adapt them if necessary, while preserving cross-country comparability.

It is also useful for addressing some of the most challenging elements to capture including: the degree to which policies are implemented and enforced (e.g. enforcement of energy efficiency standards in the building sector); the speed of obtaining building permits for onshore and off-shore renewable energy installations; the perceived stability of policies and regulations; the speed of the judicial systems in resolving disputes. Technical expertise may also be needed to gauge the impact of technological and efficiency standards on firms' investment decisions. The cost increase resulting from government regulation implies different payback period profiles for firm investments in specific technologies. Ascertaining the emission reduction potential of a given technology thus requires an in-depth understanding of the cost structure of firms operating in a given industry, which in itself can be a demanding information requirement.

The two approaches can be applied in a country-specific or a homogeneous cross-country setting:

- The country-specific approach assesses emission reductions for each country separately using a methodology tailored to each country (depending on data availability and modelling capacity). Specific elements relevant to assessing policies' effectiveness in reducing emissions can be evaluated also relying on expert judgment where needed. These may include the existence of exemptions, the level of enforcement and other policy variables that may be difficult to quantify. The methods to evaluate each policy or policy package may include different types of econometric analysis or economic and engineering models, depending on data availability. For instance, for an ex-post regression, Dussaux (2020[19]) evaluates the impact of the EU ETS using granular French firm-level data. Relying on a suite of ex-ante analytic and sector-specific models complemented by empirical estimates of response elasticities and sector-specific expert judgement, PBL (2016[20]) evaluates emission reductions in different sectors in the Netherlands of a large range of policies and policy packages (Box 7). These estimations then fed into the Dutch Biennial Report (EZK, 2019[21]). South Africa's Biennial Update Report uses a country-specific economy-wide model to assess emission reductions across 25 policies (DFFE, 2021[7]).
- The homogeneous cross-country approach estimates emission reductions relating to a set of policies common across countries. This approach yields estimates more amenable to cross-

country comparisons than country-specific ones at the cost of sacrificing potentially important country- and policy-specific details. This approach can provide broad-brush comparisons, which more detailed analysis can refine. It can be implemented either by estimating ex-post regressions or using the ex-ante analytical models. An example of the former is the work by Galeotti, Salini and Verdolini (2020[22]), who assess and compare the impacts of different environmental policy stringency indicators on energy efficiency and innovation using cross-country regressions. An example of the latter is OECD analysis employing the ENV-Linkages model, which uses a harmonized set of assumptions to assess emission reductions of changing climate policies across macro-economic sectors and regions in a Computable General Equilibrium model (Chateau, Dellink and Lanzi, 2014[23]). Another example is the IEA's Global Energy and Climate Model, which assesses emission reduction of various climate policies across countries (or broad regions) and sectors using a combination of sector-specific partial equilibrium models, covering the energy sector (IEA, 2021[24]).

The two approaches can also differ in the scope and resources they require. The homogeneous cross-country approach focuses on collecting information on the same policy elements and evaluating their effect on emission reductions within a common framework applied to each country. Accordingly, the cross-country approach can be less resource intensive, especially when it relies on regression analysis. In contrast, the country-specific approach relies on models tailored to each country (and often sector) and on identifying the relevant information to feed them. It thus usually requires specific and resource-intensive modelling capacity.

Ex-ante analytical approach

The ex-ante analytical approach can provide estimates on the effect of policies on economic activities and, consequently, the GHG emissions resulting from these activities. This approach relies on economic theory, information on a country's economic structure and energy mix, and empirical estimates of behavioural responses. Various models, differing along several dimensions such as their geographical and sectoral granularity, are available. Choosing a model implies determining the richness of the analysis, including its ability to deal with a wide range of policies and to characterise the specificity of a sector, country or technology. Granular models are richer but harder to apply systematically across several countries and sectors. This choice is further influenced by data availability and modelling capacity.

This section discusses three model classes underlying the ex-ante analytical approach: 1) partial equilibrium models, including energy system models; 2) general equilibrium models, further decomposed into computable general equilibrium (CGE) models and dynamic stochastic general equilibrium models (DSGE); and 3) integrated assessment models (IAMs). The categories are not mutually exclusive as some models may fall into more than one class. In addition, some of these models can be combined, such as when a CGE model with a partial equilibrium model. The discussion below describes these model classes from a country-specific and homogeneous cross-country perspectives, and provides in-depth case studies and examples for the two countries (South Africa and the Netherlands).

Partial equilibrium models

Partial equilibrium analyses typically focus on specific markets or sectors and assume that prices (or conditions) in the rest of the economy remain constant or unchanged. More specifically, these models can feature partial equilibriums in two distinct ways, either by focussing on a specific market such as the energy market, or by only considering the supply or demand side of the economy. As such, these models can be highly granular and are able to incorporate detailed aspects of policies. For example, they often offer a characterisation of the technologies employed in a sector, including their cost, how emitting they are and how policy is able to influence their adoption. One of the shortcomings of partial equilibrium models is that they often do not reflect second-round and rebound effects. Higher energy prices could, for instance, trigger shifts in consumption, causing increased consumption of non-energy products – which could have positive or negative impacts on GHG emissions. The lack of a feedback loop to the real economy also means that these models cannot adequately address concerns over carbon taxes' effect on potential growth, income distribution, and competitiveness.

Cross-country partial equilibrium models: energy system models

Energy system models can be considered a subcategory of partial equilibrium models focusing on the key sectors producing GHGs (Nikas, Doukas and Papandreou, 2019[25]). These models provide a disaggregated representation of the interactions between energy supply and demand and the economy. They often incorporate energy sector-specific details, providing a rich account of the adoption and diffusion of various energy sources and technologies. Accordingly, such models can help assess a wide range of price- and non-price-based measures and identify the effectiveness and costs of mitigation policies and policy packages.

How models take technological changes into account, endogenously or exogenously, determines the quantification of the amount of emissions abatement policies can achieve at a given cost. Increases in carbon prices, for instance, are expected to encourage carbon-saving technical improvement, raising the future abatement level achievable at a given carbon price.[5] Models that address technological change endogenously explicitly incorporate the feedback effect of climate policy on carbon-saving technical change. As technology development and diffusion are not linear processes, it is difficult to extrapolate their trends from past data.

One of the disadvantages of energy models is that most of them do not have a link with macroeconomic variables. Most energy models describe energy system flows in volumes and do not rely on value (nominal) data as economic models do. As such they do not consider the effect that changes in wages, costs of capital, interest rates and other variables have on energy uses and technology choices, and hence on emissions (Nikas, Doukas and Papandreou, 2019[25]). This is not an issue when energy and climate policies are limited and moderate in scope. But when they are ambitious and far-reaching (as the emission reduction targets countries have set require), they are likely to have non-negligible effects on macroeconomic variables that will bear on energy and technology choices (Greening and Bataille, 2009[26]).

Many energy models were initially developed for energy resource planning purposes and to guide energy policy. These often consisted of single-sector accounting tools, but they evolved into complex, dynamic optimisation and simulation frameworks for energy and climate policy appraisal (Nikas, Doukas and Papandreou, 2019[25]). The discussion below covers three such models: the IEA's Global Energy and Climate Model, MARKAL/TIMES, and the more recent Energy Policy Simulator.[6]

The IEA's Global Energy and Climate Model is an energy system model used for the IEA World Energy Outlook (2019[27]) (Box 5). The emissions projections from the IEA World Energy Outlook serve as an important input to several models (multi-country and country-specific models) as a baseline projection of emission reduction potential of current policies. For instance, the IPCCC sectoral estimations of different

[5] This feedback effect not only occurs through energy prices, but also for instance through research and development activities, and accumulated production experience (learning-by-doing).

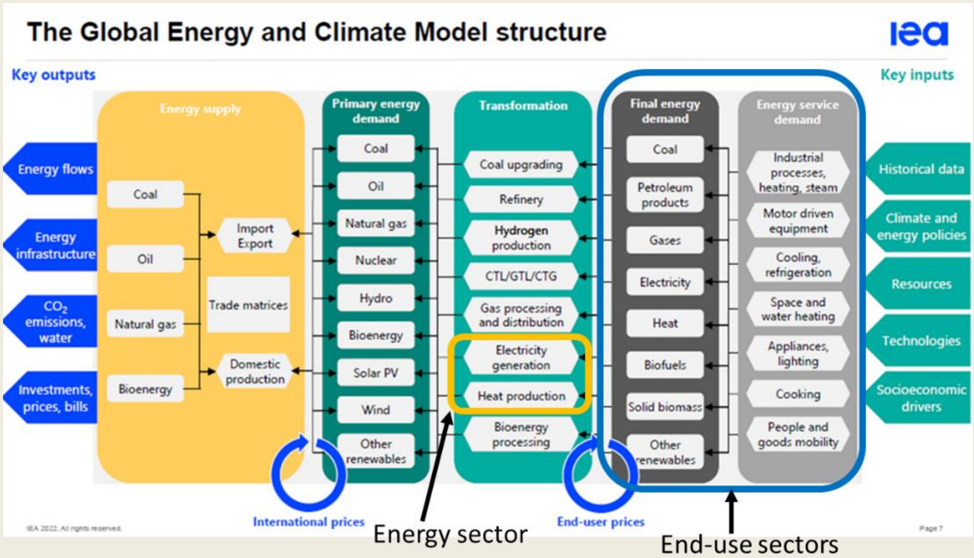
[6] This list of models is far to be exhaustive. The Integrated Assessment Model Consortium (IAMC wiki - IAMC-Documentation (iamcdocumentation.eu)) provides a list and details of such models.

climate scenarios rely on the IEA's figures covering energy, industry, and building sectors (IPCC, 2022[28]). Similarly, UNEP's emissions gap reports (UNEP, UNEP-CCC, 2020[29]), Climate Action Tracker and PBL's NEV-RES all benefit from the IEA's estimates as inputs. The IEA's Global Energy and Climate model is also used to analyse the diffusion of less carbon-intensive technologies in energy markets.

Box 5. The IEA's Global Energy and Climate Model

The IEA's Global Energy and Climate Model encompasses multiple sectoral partial equilibrium models covering different countries or geographical regions and sectors. Each sectoral module quantifies the effects on energy demand and GHG emissions from the power sector and five major end-use sectors (industry, buildings and services, transport, agriculture, and non-energy use of energy commodities) (Annex B). Assumptions on technology adoption vary across policy scenarios depending on assumed technology characteristics, such as technology cost and efficiency that are set exogenously. Figure 3 shows the model structure with key inputs (e.g. climate and energy policies, technologies, socio-economic drivers) shown on the right and key outputs (energy flows, GHG emissions, etc.) on the left. The IEA model uses detailed country-level information on existing and planned policies to quantify the effects of policy packages on GHG emissions. It also uses granular information on costs, including technology, labour, and capital costs. For example, for the oil and gas sector, the IEA incorporates detailed estimates on abatement costs from oil and gas leakage detection and repair to assess the effect of policies aiming at reducing leakages (IEA, 2021[24]; IEA, 2022[30]).

Figure 3. The IEA Global Energy and Climate Model structure



Note: The figure shows the structure of the IEA Global Energy and Climate Model.
Source: IEA.

The IEA can apply several scenarios to evaluate the effects of policies or policy packages on emissions. Its Stated Policies Scenario (STEP) takes a granular, sector-by-sector view and includes existing policies and measures and those that are under development, including pricing policies, efficiency standards, electrification programmes and infrastructure investment programmes. An alternative approach is taken in the IEA's Announced Pledges Scenario (APS), which assumes that all climate commitments made by governments, including Nationally Determined Contributions and Net Zero targets will be met on time. The APS thereby assumes that all targets and pledges will be converted into policies to achieve the pledged emission reductions.

Other multi-country partial equilibrium models have been developed, often in collaboration with the IEA, including the MARKAL/TIMES model and the Energy Policy Simulator.[7] MARKAL's input data can be tailored to represent the evolution of a specific energy system at the national, regional, state or province, or community level. It is currently used in 70 countries by 250 institutions. MARKAL is a comprehensive model, with 1500 technology types, 250 energy carriers plus constraints, taxes, emissions and other model parameters. The model has well over 500 000 data elements. The MARKAL model has been used to study a wide range of climate policy questions related to, for instance, the most cost-effective carbon emission control strategies for China (Chen et al., 2007[31]), optimal use of biomass in Western Europe for greenhouse gas emission mitigation (Gielen et al., 2001[32]) and the effects of technology learning for renewable energy generation in South Africa (Winkler, Hughes and Haw, 2009[33]).

The MARKAL/TIMES model selects a combination of technologies that minimise total energy system cost under various physical and policy constraints. It is also highly relevant to investigating the development of less carbon-intensive technologies and looking at the conditions for the adoption of these technologies. MARKAL depicts the entire energy system from imports and domestic production resources (fossil and renewable), through fuel processing and supply (e.g., refining, bio-processes), explicit representation of infrastructures (e.g., gas pipelines), conversion of fuels to secondary energy carriers (including electricity, heat and hydrogen), end-use technologies (residential, commercial, industry, transport, agricultures, non-energy), and energy service demands (at a sub-sectoral level), taking into account uncertainties surrounding fossil fuel prices or emission constraints.

The basic components of the MARKAL/TIMES model are distinct energy or emission reduction technologies, each quantitatively represented by a set of performance and costs characteristics. The cost minimizing feature of the model takes into consideration the evolving costs and features of these technologies as well as those of resources, infrastructures, taxes, and conservation measures - in order to meet energy service demands. Unlike some other energy system models, MARKAL does not require or permit an a priori ranking of greenhouse gas abatement measures as an input. Rather, the model selects the preferable technologies and generates the resulting ranking.

The Energy Policy Simulator, developed by the "Energy Innovation" think-tank, is an open-source forward-looking energy and climate policy model that can run annual simulations up to 2050 (Energy Innovation, 2022[34]).[8] It exists for nine countries and several sub-national jurisdictions[9] Box 6 discusses the Energy Policy Simulator in more detail.

Box 6. The Energy Policy Simulator

[7] The initial model referred to as MARKAL has been developed since 1980 and its successor, TIMES, since 2000.

[8] The Energy Policy Simulator is available here: https://us.energypolicy.solutions/scenarios/home (United States version).

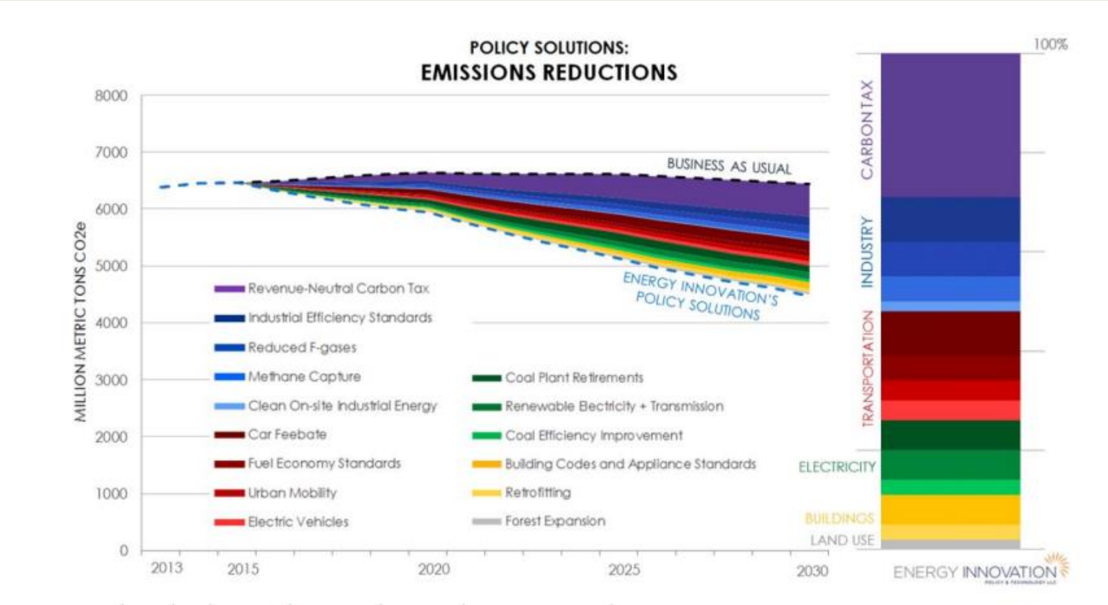
[9] The Energy Policy Simulator has been calibrated for Brazil, Canada, China, India, Indonesia, Mexico, Poland, Saudi Arabia and the United States. It exists also for several US states, the Canadian Province Alberta, as well as for Hong Kong and Zhejiang.

The Energy Policy Simulator combines the impacts of policies on energy use, CO_2 equivalent emissions (CO_2e), technology deployment and the economy (GDP, jobs, etc.). The model does not endogenously determine energy demand but instead relies on outputs from other models covering energy and services demand. For example, for the electricity sector in the United States the model uses data from the Annual Energy Outlook of the US Energy Information Administration as input and subsequently decides how to meet the demand based on information on technology costs, grid flexibility constraints and other factors. It uses information on levelised cost of electricity from different sources to determine the amount and type of new power plant additions. In the transport sector, the Energy Policy Simulator uses service demand (in terms of passenger-miles or freight-miles) as exogenous input data. Using data on the total cost of vehicle ownership and non-monetary barriers to technology adoption (e.g. reduced range with electric vehicles), the model optimizes the deployment of new vehicles to meet the service demand.

The Energy Policy Simulator provides policy options or policy targets to model technology adoption, which in turn affect energy demand and emissions. For example, it allows setting mandates on the share of zero-emission vehicles for a specific year or phasing out new coal power plants. While the model allows estimating emission reductions from such non-price-based policies, it relies on assumptions of full implementation and deployment. For example, emission reductions from a clean electricity standard assume that this standard is met in the specified year, regardless of its stringency, time horizon or complementary policies. It may therefore provide an upper bound on emission reductions compared to other models that allow for more flexibility with less than full policy implementation and compliance.

Figure 4 shows an example result of the output from the Energy Policy Simulator, comparing BAU emissions to alternative scenarios that vary by the type of policy, including a revenue-neutral carbon tax (purple), industry energy efficiency standards (blue) and residential building standards and retrofitting policies (yellow) (Energy Innovation, 2022[34]).

Figure 4. Example results produced by the *Energy Policy Simulator*



Note: The figure shows an example result produced by the Energy Policy Simulator
Source: Energy Innovation (2022[34]).

Country-specific partial equilibrium models: the case of the Netherlands

Netherlands Environmental Assessment Agency (PBL) relies on a wide variety of sectoral models for the environmental policy evaluations of the Netherlands. All different sectoral models are interconnected in an overarching system: the Netherlands National Energy Exploration Calculation System (NEV-RS). The NEV-RS is a system that manages the coherence and communication between various models that have been developed for making projections for Dutch energy use and the associated sectoral emissions of GHGs (Box 7).

Box 7. Country-specific estimation of emission reductions for the Netherlands

Table 1 lists the 14 different models and tools that are interconnected in the Netherlands National Energy Exploration Calculation System (NEV-RS) to estimate emission reductions attributable to policies. The emission reductions are estimated using a combination of quantitatively estimated elasticities, as well as sector-specific expert judgement to calibrate the model and complement quantitative information. For example, modelling policy enforcement and compliance can require in-depth knowledge of the capacity of regulatory agencies to control policy compliance.

Table 1. Models and tools used in the Netherlands NEV-RES model

#	Name of model or tool used as input in NEV-RES	Description	#	Name of model or tool used as input in NEV-RES	Description
(1)	Energy prices	Energy prices of gas and electricity	(8)	SAVE-Production	Energy consumption of industry and agriculture, including the use of conventional decentralized cogeneration installations in all sectors
(2)	Mobility	Various models are used for estimates of changes in mobility and uncertainties	(9)	Heat	Heat supply to and from the industrial sectors and agriculture
(3)	Gas and oil extraction	Extraction of gas and oil on Dutch territory and the associated consumption of energy	(10)	COMPETES	Electricity production, electricity prices, CO_2 emissions and electricity trading between individuals European countries
(4)	SAWEC	Home-related energy consumption	-11)	Resolve-E	Deployment and production of renewable energy
(5)	EVA	Electricity consumption of household appliances	(12)	SELPE	Checking whether all individual models have provided a consistent dataset
(6)	SERUM	Energy consumption and emissions from the refining sector	(13)	Monit-Conversion	Converting detailed results at process and sector level to the desired format, and calculations of energy savings
(7)	SAVE-Services	Energy consumption of the service sector	(14)	MONIT	Storage and presentation of results

Note: The table lists the models used in the Dutch NEV-RES model.
Source: PBL https://www.pbl.nl/modellen/kev-rekensysteem.

PBL's estimation of the abatement impact of policies comprises several steps. It first establishes a baseline against which to assess future GHG emissions by, for instance, updating the developments of relevant exogenous factors including developments in the economy, demographics, technology, energy systems and fuel and CO2 prices. The latter, for instance, is computed using both the energy price model (1) and COMPTES (10) (Table 1). The subsequent step involves considering the expected developments in sectoral activity such as in manufacturing (8), housing and building stock (7) and transport, i.e. the number of kilometres driven (2). These expected sectoral developments allow for calculating the demand for energy, such as that for electricity, gas, or fuel. Then, the availability and costs of different energy sources (i.e. fossil fuels, nuclear energy, renewable source electricity generation) allow for assessing how the energy demand will be met, as well as, the effects of policies hindering or encouraging different types of energy. The energy use of different sectors feed then into the calculation of their GHG emissions. In addition to energy-related emissions, there are also process-related emissions, such as those from industry, livestock and arable farming and land use.

The SAVE-Production model: one of the models within the NEV-RS

The SAVE-Production model is a model of the Dutch industry and horticulture, including combined heat and power (CHP). It is a dynamic model including investments for the coming decades. The model's output includes energy use per subsector of the Dutch industry and horticulture, GHG emissions and investments in new production technologies, CHP installations, and energy and GHG reduction options. The output is also regularly used to calculate air emissions such as SO2 and NOx. Future production per industrial subsector is an exogenous input to the model.

The model consists of two main modules. The first module calculates for each target year for the different industry and horticulture sectors the demand for heat for industrial processes and electricity demand such as for lighting. The demand for heat is derived from the assumptions about future production developments (such as, for example, the development of the production volume of paper in the paper sector). In this module, the effects of energy-saving policies on energy consumption are also calculated. Ingrowth of energy saving techniques is modelled based on the assumption that a technology's performance typically shows slow initial improvement, then accelerated improvement and finally diminishing improvement with respect to effort or money invested in the technology (the so called "s-curve approach")

The second module calculates the investments in and the operational use of CHP-installations in order to meet heat demand and production levels. This module has been completely revised in the last two years reflecting new technologies and emission reduction options. Furthermore, it has been adapted to include new policy instruments such as the Dutch marginal CO_2 levy for industry. It is an optimization model in which firms' costs are minimized. The cost minimization takes into account the availability of subsidies and levies, such as the sustainable energy production subsidy (SDE++), the Dutch CO_2 tax, the EU ETS, and other energy taxes and network tariffs. The optimization is dynamic, considering multiple years into the future while allowing the model to choose the optimal investment moment and taking into account (variants of) technologies as they become available.

The granularity of PBL's sectoral models facilitates the estimation of emission reductions of individual policies, including non-price-based policies. However, the order in which individual policies are introduced matters for the estimation of emission reductions. Therefore, such a model may be more suitable to evaluate the effectiveness of policy packages if a clear sequencing of policy reforms is not available.

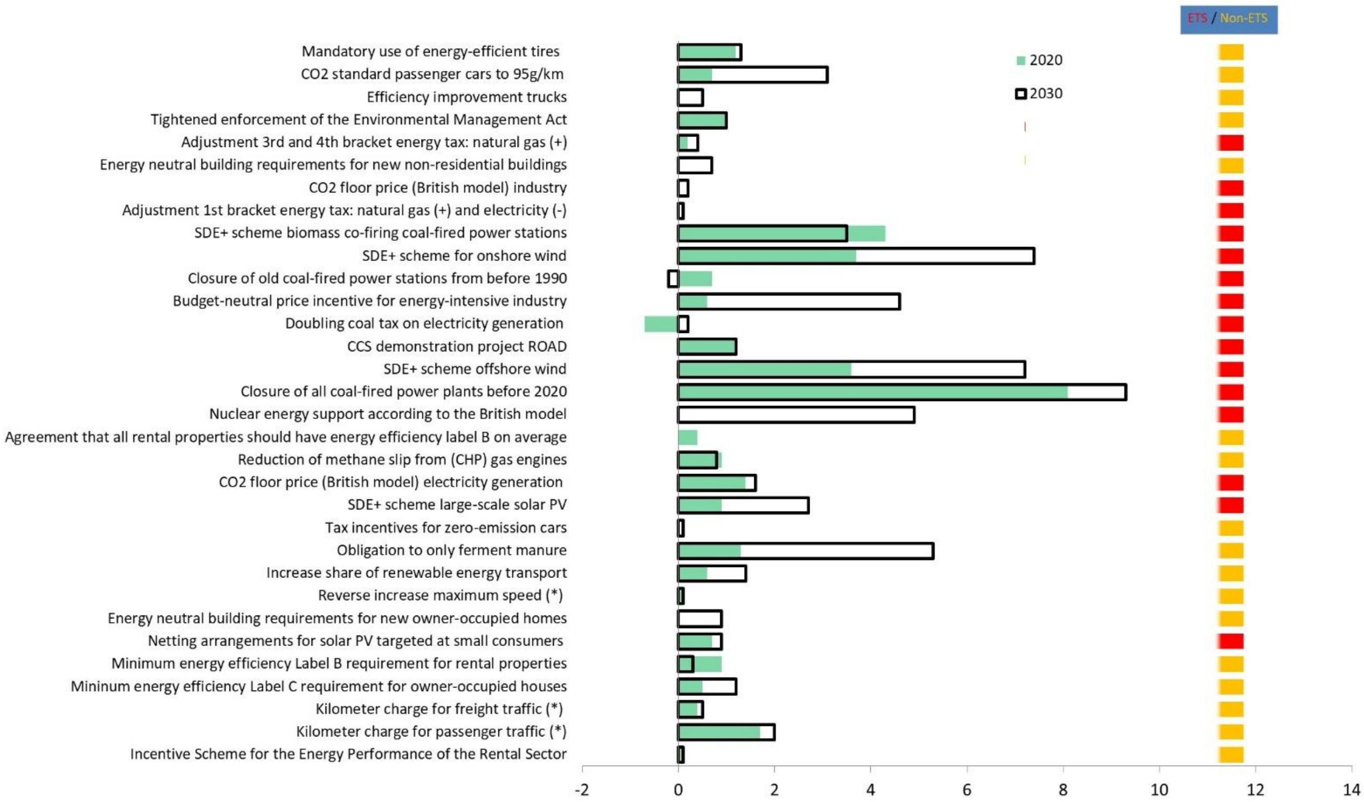
PBL (2016[20]) analysed the individual effects and costs of 34 policy measures, including measures to promote clean technologies.[10] Figure 5 shows for each policy the CO_2 emissions avoided (in Mton/year) for 2020 and 2030. Closing all coal-fired power plants by 2020 results in the largest emission reduction of nearly 9Mton/year for both 2020 and 2030. As part of the Dutch SDE+ program that incentivizes clean

[10] This study relies on a different model than outlined in Box 7. The NEV-RES model system would, however, be able to provide similar results as depicted in Figure 5.

technology, auctions (also known as "call for tenders") for wind (onshore and offshore) account for the second-largest reduction in emissions. Due to the time lag from auctions permissions and the construction of the wind parks, the effects are estimated to be twice as large in 2030 compared to 2020 (in annual emission reductions). The effects of a policy package (i.e. a combination of individual policies) are generally lower than the sum of the effects of individual measures. For instance, the combined effect of subsidizing biofuels and electric cars is lower than their separate effect due to trade-offs between fuel and electric cars usage.

Figure 5. Estimated effectiveness of Dutch climate policy measures

CO_2 emissions avoided in Mton/year



Source: PBL (PBL, 2016[20]).

General equilibrium models

Macroeconomic general equilibrium models provide an analytical description of an economy's equilibrium in several markets, either in a static or dynamic environment, and in a single or multiple country setting. The main advantage of this type of models is that they are able to take into account the interactions between sectors and countries via production structures and international trade for different policy options and packages. General equilibrium models tend to integrate price-based instruments more easily than non-price-based instruments. This is because the modelling of different sectors and technologies may not be granular enough to accommodate many non-price-based instruments (such as standards and regulations). Their integration can also prove difficult for the solution of the model since non-price-based policies can translate into nonlinear functions that are difficult to solve. Nevertheless, it is still possible to do so. There are two primary categories of general equilibrium models: Computable General Equilibrium (CGE) models and Dynamic Stochastic General Equilibrium (DSGE) models.

Country-specific models can integrate a larger set of policies since they tend to represent its sectors at a finer resolution than models that incorporate multiple countries. The greater the sectoral and geographical level of aggregation, the more restricted the types of policies that can be implemented. In addition, country-specific models can more easily solicit expert judgement to inform on the particularities of certain regulations or technologies in the concerned jurisdiction.

In climate policy analysis, general equilibrium models may incorporate four types of emission reduction options: 1) output-demand reduction; 2) factor substitution; 3) input substitution; and 4) installation of abatement equipment other than fuel substitution, for instance by employing energy-efficiency enhancing technologies (see Kiuila and Rutherford (2013[35])). While the first alternative is straightforward, the last three are more complicated to model. To cover the final three possibilities in a single function, IAMs establish an abatement cost function in which firms can lower their emissions by paying an abatement cost which is proportional to their output. CGE models can address the first three alternatives for reducing energy-related emissions endogenously, without the requirement to establish an abatement cost function. Some DSGE models, such as the EQUEST model developed by the European Commission (see below), can also address the first three alternatives without the requirement of establishing an abatement cost function.

Computable General Equilibrium models

CGE models employ an analytical description of an economy's general equilibrium in several markets. The calibration of the model's prices, wages, and exchange rates to historical data relies on national accounts data (such as domestic consumption, output, trade flows, and taxes) and elasticity estimates. In addition, their calibration may also rely on projections from partial equilibrium models and expert judgement. CGE models often provide a rich sectoral representation of the economy and can depict the complex interrelations between sectors. Unlike IAMs, CGE models do not attempt to discover the ideal trade-off between climate and the economy; rather, they try to shed light on the economic consequences of climate change and specific policies or policy packages to mitigate it (Rivera et al., 2017[36]).

CGE models are used to evaluate the impact of a change in one or more of the exogenous parameters (like policy tools) of the economy by computing a new counterfactual equilibrium. Comparing the new counterfactual equilibrium to the initial equilibrium provides insights into the effect of a "shock" to the economy. CGE models' climate scenarios are typically exogenous, and shocks are introduced into production functions. For instance, a reduction in crop yields due to flooding will exogenously be reflected in the agricultural production function through alterations in the supply of agricultural products (Sue Wing and Lanzi, 2014[37]).

Through sectoral linkages, CGE models are able to trace the full (or general equilibrium) impact of a policy change on the different and interdependent sectors of the economy. This is one of the main advantages of CGE models relative to partial equilibrium models (focusing on a single sector) and other models without a multi-sector representation of the economy. Some partial equilibrium models can however be linked to CGE models, thus enhancing the level of sectoral detail the model can integrate. This leads to varying coverage of climate policies (price-based and non-price-based) across CGE models (Annex C, Table 1).

Although CGE models often contain numerous energy sources, they lack the complex interactions between energy technology and mitigation policies found in energy system models. Generally speaking, most CGE models treat technological change exogenously, potentially overestimating the abatement costs and underestimating the effect of price-based policies on emissions. Another limitation of CGE models is that they deal only partially or not at all with dynamics, market frictions, and uncertainty. Hence, they are better suited to study stable long-horizon scenarios. They are not suited to study off-equilibrium adjustments, i.e., the transition to the new equilibrium.

To illustrate these approaches, the discussion below focusses on three CGE models and their applications. These include one global cross-country model (ENV-Linkages) as discussed in Box 8 and two country-specific models (Denmark and South Africa), as discussed in Box 9 and Box 10 respectively.

Box 8. ENV-Linkages: a global cross-country CGE model

The OECD's ENV-Linkages is the primary modelling tool used at the OECD to examine the relationship between the economy and the environment (Château, Dellink and Lanzi, 2014[38]). It is maintained and developed by the Environment Directorate. ENV-Linkages is a direct descendent of the OECD GREEN model hosted at the OECD's Economics Department in the 1990's. ENV-Linkages is a multi-country, multi-sector CGE model that links economic activity to drivers of environmental pressure and projects sectoral and macro-economic variables and indicators. The regional aggregation of the model varies according to projects and ranges between 15 and 25 countries, as it is limited by data and computational constraints. The regional aggregation is however flexible and, when country-specific data is available, other countries can also be isolated, increasing the number of regions in the model (see for instance (OECD, 2021[39])).

ENV-Linkages is used to develop a variety of global, regional and country-specific scenarios and to analyse the macroeconomic and environmental implications of policies targeted at the transition to a low-carbon economy as well as other environmental issues. While ENV-Linkages has most often been used to study the effects of price-based policies, it has recently been used to study the effects of regulations in the context of air quality improvements and plastic pollution (OECD, 2022[40]; OECD, 2016[41]). An integrated assessment can be achieved by linking ENV-Linkages to IAMs that describe the biophysical consequences of environmental pressure. Such linking has been done in the OECD Environmental Outlooks, where ENV-Linkages was coupled to the IMAGE suite of models operated by PBL Netherlands Environmental Assessment Agency.

ENV-linkages' macroeconomic closure and comprehensive description of economic sectors helps to account for complementarities and substitutabilities of different climate policy tools, hence preventing double accounting of emission reductions. Moreover, the representation of international trade enables to account for carbon leakage and spill over effects of climate policies across countries. But the model's lack of sectoral and technical granularity and the inadequate representation of some economic behaviours (transportation choices), risks a misevaluation of the effectiveness of some policies. A possible way to address this would be to use information from more granular partial equilibrium models as input to ENV-Linkages to improve the representation of some sectors and technologies (for instance CCS technologies and a transportation module).

Box 9. GreenREFORM: a CGE-model for Denmark

GreenREFORM is a climate-economic model currently in development for the Danish economy. The GreenREFORM model consists of a main dynamic computable general equilibrium model (CGE-model) and several sub-models that describe sectors in the economy that are particularly important in terms of climate and environmental impact (i.e. transport and agriculture).

The development of the GreenREFORM model started in 2017 with the ambition to design a fully integrated model system where all sub-models and the main model are linked and solved simultaneously. The model will be able to describe the effect on emissions from environmental taxes, subsidies and command-and-control regulations. Although the model is still in development, the project has progressed enough to provide preliminary results on the effects of a uniform carbon tax and the EU ETS system. GreenREFORM includes a detailed description of different pollution reduction methods available through investment in specific technologies. It will endogenously describe how new cleaner technologies can displace existing technologies over time, depending on the policies in place.

GreenREFORM will be able to describe the emission of pollutants in the Air Emissions Account produced by Statistics Denmark from all Danish businesses, households and the public sector. The model can produce yearly forecasts for each year up to 2100, and has a highly disaggregated nature. It consist of 59 sectors and includes 27 different energy products, for example, oil, gas, and biomass, aggregated from 52 different products in the data.

There are several CGE models calibrated to the South African economy, explicitly taking into account the linkages between the economy, the energy system and emissions. These models are able to project the effects of several policy levers, including refined futures of the policy under consideration. They differ little in the modelling assumptions, while considering different scenarios beyond the introduction of a carbon tax, ranging from changes in energy efficiency and structural shifts in energy supply (Pauw, 2007[42]), to the introduction of a carbon border adjustment (Alton et al., 2014[43]) and different types of revenue recycling (Van Heerden et al., 2016[44]). A good example of a study that exploits the greatest strength of CGE modelling is the one by Partnership for Market Readiness (2016[45]), discussed in detail in Box 10.

Box 10. Evaluating the impact of South Africa’s carbon tax employing CGEs

A study by Partnership for Market Readiness (2016[45]) models the exact features of the South African carbon tax as actually implemented, closely reflecting its scope, level, and rebate structure. The study exploits the greatest strength of CGE modelling - the detailed sectoral disaggregation - to show the heterogeneous effect of a carbon tax across sectors, but also it highlights the challenges in adapting standard CGE models to take into account environmental and climate-policy considerations.

The scenarios Partnership for Market Readiness considered include a wide range of policy choices, encompassing a gradually increasing sector-specific carbon tax and sector-specific tax-free allowances, while also taking into account revenue recycling towards producers (through tax rebates) or consumers (through a reduction of the VAT). In the reference scenario (gradually removed rebates and revenue recycling), the study shows that the proposed policy yields large emission reductions (-33% in 2035) while effects on GDP are modest (-3% in 2035).

As with any other analysis on mitigation policy effectiveness, this study delimits its scope and makes simplifying assumptions to keep the model tractable and the results interpretable. These choices can be investigated according to the criteria established in the first section. First, the study focuses on a wide range of GHG emissions from the combustion of fossil fuels and industrial processes, but disregards fugitive emissions (such as those from mining activity) because of data limitations. Second, it ignores the combined effects of overlapping policies, particularly stemming from company-level carbon budgets, which will be implemented in their definitive form only in 2023, and the regulation for carbon offsets. Third, the study establishes two alternative baselines with which to compare the policy scenarios. These baselines make different assumptions about macroeconomic variables.

For its study, Partnership for Market Readiness exploited and enhanced an existing CGE model: the University of Pretoria's General Equilibrium Model (UPGEM). Creating and calibrating such a model is a difficult task requiring specialised technical skills, time and data (at the minimum, detailed input-output tables and an environmental accounting matrix). The motivation for the changes to the standard UPGEM model was to enable a more accurate and detailed analysis of the energy sector in South Africa, in particular concerning changes in the electricity generation mix and measurement of carbon emissions. The changes included: i) the inclusion of an energy and gas emissions accounting module; ii) equations that allow for inter-fuel substitution in electricity generation; and iii) mechanisms that allow for the endogenous take-up of various abatement measures in response to GHG policy measures.

Dynamic Stochastic General Equilibrium models

Dynamic Stochastic General Equilibrium (DSGE) models consider dynamics and sources of uncertainty in a general equilibrium setting. Most DSGE models feature fully forward-looking intertemporal optimisation which is missing from the widely used static or recursive-dynamic CGE models.[11] DSGE models sacrifice the number of regions and sectors modelled for a richer economic structure. Their main advantage is that they allow to explore the dynamics of an economic system and the adjustment path towards a new equilibrium by capturing time-related frictions, such as nominal rigidities, borrowing constraints, investment adjustment costs and consumption habits. DSGE models are thus better able to reflect short-term dynamics (the adjustment path) compared to CGE-models. Also, DSGE models deal with uncertainty better than CGE models by incorporating stochastic shocks with different level of persistence. Their main drawbacks are that they are computationally intensive and can consider fewer sectors, countries and climate policy instruments than CGE models.

Annicchiarico and Di Dio (2015[46]) provides one notable example of a DSGE model that combines environmental pressures and macroeconomic dynamics. Alongside implementing some standard features of DSGE models, i.e. nominal price rigidities and capital adjustment costs, the model includes emissions which are by-products of output. Emissions are assumed to be costly; hence firms are inclined to limit the environmental impact of their production activity by undertaking abatement measures. The model's rich representation of economic frictions allows it to provide insight into various environmental and economic issues, such as the extent to which nominal rigidities influence the macroeconomic effects of climate policies or the impact of the monetary policy regime on the optimal environmental policy response to shocks. The rich economic structure of the model however limits the number and variety of climate policies it can consider. The model only distinguishes between three types of environmental policy instruments: a cap-and-trade system (i.e. an exogenous limit on aggregate emissions), an emission intensity target (i.e., an exogenous limit on emissions per unit of aggregate output) and a carbon tax.

The European Commission developed a micro-founded DSGE model (E-QUEST) with energy sectors particularly calibrated to the European Union (Varga, Roeger and in 't Veld, 2021[47]). Although EQUEST has much less sectoral detail and regional disaggregation compared to large-scale CGE models, it

[11] Forward-looking optimisation allows for a more rigorous modelling of investments in physical and financial assets and the domestic and foreign debt accumulation. This feature also allows for the inclusion of comprehensive monetary and fiscal policy rules together with forward-looking interest parity conditions for modelling the price, interest rate and foreign exchange rate dynamics.

introduces some sectoral disaggregation allowing it to address climate policy measures targeting dirty and clean sectors. It distinguishes seven sectors: two energy provider sectors, three tangible capital producing sectors and the rest of the economic activities are allocated into two sectors depending on their emission intensity. The model only accounts for three different policy instruments: carbon taxes, subsidies and emission limiting regulations (without direct fiscal revenue). The model is, however, able to study the effects of different revenue recycling schemes, for instance by means of reducing distortive taxes. Varga, Roeger and in ’t Veld (2021[47]) applied the E-QUEST model to the European Union and found that the costs of moving towards a net zero emissions economy can be significantly reduced when carbon taxes are used and are recycled to reduce other distortive taxes, or for subsidising clean energy.

Integrated Assessment Models

The key feature that turns an economic model into a fully integrated assessment model (IAM) is the link between certain geophysical variables affecting climate change and the economy. Such a link can consist of a carbon cycle, a radiative forcing equation, climate change equations and a climate-damage relationship (Nikas, Doukas and Papandreou, 2019[25]). While there exist in the literature different criteria for considering a modelling framework as an IAM, the DICE model (Nordhaus and Yang, 1996[48]) is considered as one of the earliest and most representative IAM models. DICE is a welfare optimisation model in which economic agents substitute present consumption for preventing climate change in the future. DICE is a fairly simple, transparent and highly aggregated model which represents the economy as a single all-encompassing sector. It is particularly useful to shed light on the relationship between economic activity, climate change and the resulting damages from climate change. Stricter climate policy entails costs by means of reduced output. Climate change is modelled endogenously through equations linking emissions to the temperature level. Higher temperature levels in turn affect GDP by means of a monetary damage function that relates temperature anomalies to GDP losses. Many IAMs have built on DICE adding more complex features of the climate and the economy.

IAMs are usually developed from a global or highly regionally aggregated perspective, limiting the variety of climate policies that can be studied, and are thus less suitable for single-country analysis. Other important limitations of IAMs include an over-reliance on optimal policies and technologies to be deployed to reach net zero targets (Gambhir et al., 2019[49]), assuming exogenous technological change, a deterministic approach to uncertainty (i.e. modelling uncertainty as ex-ante known scenarios), and an inability to account for tail risks (Pindyck, 2017[50]).

The Integrated Assessment Modelling Consortium provides a repository of documentation of the several IAMs and other modelling frameworks developed around the world. It tracks several aspects of the models that are part of the consortium, including the geographical scope, the solution concept and the policies the models can assess. Several models in this repository study the impact of price-based and non-price-based policies.

Another prominent example of an IAM is the IMAGE framework built under the auspices of the Netherlands’ Environmental Assessment Agency (PBL) (2021[51]). It addresses a set of global environmental issues and sustainability challenges. The model can assess the impact of both price-based and non-price-based measures such as portfolio, emissions and energy efficiency standards. While IMAGE maintains an intermediate level of complexity both along the environmental and economic dimensions, it provides more limited coverage of measures than a country-specific model such as the Brazilian Land Use and Energy System (BLUES) model.

Ex-post empirical approach

Ex-post empirical approaches can be used to complement the ex-ante analytical approach in several ways. For instance, they can empirically test the model assumptions, guide the model choice and quantify past effects of a policy to be compared with the ex-ante analysis, providing estimates of the impact of past policies at different levels of aggregation. Moreover, ex-post empirical approaches can be used to estimate elasticities (including emissions elasticity to policy, the elasticity of fuel demand to price, elasticities of substitution of production inputs, etc.) to parameterise analytical models. For example, D'Arcangelo et al. (2022[52]) use granular information on a large panel of countries and industries to estimate the elasticity of emissions and tax revenues with respect to price-based policies.

The regression methods discussed here include: 1) country-specific regression approaches; 2) cross-country approaches based on policy indicators; and 3) cross-country approaches based on comparisons of emission trajectories. Cross-country methods can be used to estimate average effects but often fall short of precisely identifying the causal effects of an individual policy in a specific country. In contrast, country-specific regression methodologies using micro-data can be used to credibly identify the effect of a policy, as well as to overcome problems of data comparability. However, these methods require some exogenous variation in treatment, such as a comparable group not affected by the policy. As this condition is difficult to meet, systematically applying country- and policy-specific regressions as a stand-alone approach to all policies in all countries is not feasible.

Data requirements for ex-post empirical analysis increase quickly with the scope and the level of detail of the analysis, with the highest requirements for country-specific regression approaches. A cross-country regression approach has the advantage of requiring relatively little data, albeit a trade-off exists between exhaustiveness and data comparability. The data requirement is minimal when the evaluation approach consists in mere comparisons of emission trajectories, such as emission intensities. For example, comparing cross-country differences in emission reductions over a certain period as a proxy for policy stringency has low levels of data requirements because no information on individual policies and their level of stringency is required (Young, 2022[53]). The data requirement is somewhat higher for regressions using policy indicators, for example using data at the country-sector level, because information on policies and their level of stringency needs to be included explicitly in the regression analysis.

In contrast with the ex-ante modelling approach discussed above, the ex-post regression approach usually does not require data on abatement costs nor does it explicitly model the evolution of abatement costs. Rather, econometric analyses can be used to infer abatement costs from estimates of the responsiveness of emissions to policies. This information on responsiveness and historical abatement costs can be used to calibrate and enrich ex-ante modelling.

Being based on historical data, regressions necessarily provide a snapshot of past policies' effectiveness and have limitations when used for forward-looking assessments. In particular, regression analysis does not capture the effects of future advancements in abatement technologies. If low-carbon technologies become more affordable and abatement costs decrease, mitigation policies will become more cost-effective. Technological advancements are themselves a function of mitigation policy, which further complicates forward-looking analysis on technology development and diffusion. Trends can be extrapolated from data on technology adoption or abatement costs, but these data are often absent and not always a good predictor of future technology development and adoption. Ad-hoc expert judgement, such as technical expertise on the evolution of different abatement technologies, firms and industries' cost structure is key to building credible forward-looking scenarios based on ex-post regression estimates.

Country-specific regression approach

Country-specific regression approaches estimate the effects of policies on emissions using country-specific information on policies and emissions. Isolating the causal effects of climate policies on emissions for each country involves high data requirements, including granular micro-data (either at the firm or household level) and exogenous variation in the policy of interest. To establish a counterfactual, information for firms (or households) that are exposed to the regulation (i.e. the “treated” group) and for firms (and households) that are not covered by the regulation (i.e. the “non-treated” or “control” group) is needed.

Over the past decade, the OECD has conducted several empirical studies to quantify the impact of specific climate policies on emissions using ex-post econometric techniques (Box 11). These studies leverage historical changes in the stringency of climate policies to analyse their effects on emissions. The evidence shows that climate policies implemented in the past have significantly reduced greenhouse gas emissions. For example, the introduction of the European Union Emissions Trading System (EU ETS) led to a reduction in carbon emissions by 10% between 2005 and 2012. The French carbon tax reduced emissions by 5% between 2013 and 2018. The removal of energy subsidies in Indonesia led to declines in energy use and carbon intensity (of respectively 5% and 10%, for a 10% increase in energy prices) (OECD, 2021[54]).

Comparing evidence across studies covering different countries is an issue. Some studies gather micro-level data from various countries. Progress to ensure further comparability across countries could involve a distributed micro-data approach similar to OECD’s DYNEMP and MULTIPROD using administrative micro-data across countries.

Box 11. Empirical estimates of emission reductions from climate policies using micro-data

EU Emissions Trading Scheme

Dechezleprêtre, Nachtigall and Venmans (2018[13]) provide a comprehensive firm-level impact evaluation of the effects of the EU’s Emission Trading System (ETS) on carbon emissions and economic outcomes for a sample of 3 000 firms across European countries. They identify the causal effect of the EU ETS on regulated companies by comparing them with unregulated but similar firms and installations using a “matching” method and examining effects on firms’ emissions as well as other economic variables. The results of the study show that the emissions trading system led to a substantial reduction in emissions (10% on average between 2005 and 2012. Similar effects have also been found in country-level studies. Petrick and Wagner (2014[55]) find that regulated German firms reduced their CO_2 emissions by one-fifth between 2007 and 2010. Wagner et al., (2014[56]) find that French manufacturing firms regulated by the EU ETS reduced emissions by an average of 15-20% (see Dechezleprêtre et al. (2018[13]) for a detailed review).

French carbon tax

Dussaux (2020[19]) use data on 8 000 French firms that are representative of the French manufacturing sector and analyses the causal effect of the French carbon tax, showing that the carbon tax (which increased from EUR 5 in 2014 to EUR 45 in 2018) reduced carbon emissions by 5% compared to the counterfactual of no carbon tax. The paper also simulates the effects of further increases in the carbon tax up to EUR 86 per tonne of CO_2, showing that this would further reduce emissions by 8.7%.

Removal of fossil fuel subsidies in Indonesia

Brucal and Dechezleprêtre (2021[57]) analyse the effect of the removal of fossil fuel subsidies in Indonesia, which resulted in an increase in energy prices. Using data from the Indonesian Census of Manufacturing for Medium and Large Enterprises, the authors observe more than 70 000 manufacturing plants between 1980 and 2015. Using a panel data fixed effects estimation, they show that a 10% increase in energy prices (from the removal of fossil fuel subsidies) caused a reduction in CO_2 emissions by 5.8% on average, with a stronger effect on more energy-intensive firms.

Source: (OECD, 2021[54])

Cross-country approaches based on policy indicators

Cross-country regressions can be used to estimate the average emission reduction of a policy implemented in several countries. This typically yields a cross-country average effect and not an individual treatment effect. For this reason, these estimates are ill-suited to quantify precisely the counterfactual effect of one specific policy in a country and should rather be used to inform the policy debate across countries, formulate cross-country policy recommendations and highlight elements important for ex-ante analytical models.

Cross-country approaches based on policy indicators can help ensure data comparability across countries and tractability of the empirical model, by reducing the number of policy variables to analyse. Synthetic policy indices aggregate a wide range of information on different policies into a single figure. This approach can easily evaluate policy packages, as individual policies are summarised in the synthetic policy indicator, thus capturing synergies or trade-offs among them. At the same time, they limit the analysis to common policy characteristics or reduce the number of policies that are analysed. For this reason, policy indicators are not well suited to compare individual policies, reducing nuances, and face the challenge of comparing different policies across countries (Box 12).

Box 12. Challenges in data collection for cross-country approaches based on policy indicators

This box describes important challenges in measuring the stringency of environmental policies through policy indicators and their effect on emissions on account of the numerous and important aspects of policies that may be difficult to capture.

Multidimensionality

Countries adopt separate regulations targeting different sectors. Some regulations target specific industries, such as the EU Emissions Trading System targeting the power and some manufacturing industries. Other regulations target households or car users specifically.

Coverage

The coverage and exemptions of regulated firms, households and activities can impact the stringency of climate change regulation. For example in the EU ETS, only larger installations are regulated based on thresholds on their thermal or productive capacity. In the Netherlands, an operating subsidy for climate-friendly technologies (SDE+) was originally designed for the large-scale roll-out of technologies for renewable energy production. This scheme was expanded in 2020 (SDE++) and now also supports other technologies that reduce CO_2 or other greenhouse gases (including e.g., carbon capture and storage). South Africa provides an allowance for businesses to implement energy efficiency savings in the form of a tax deduction (12L Tax Incentive). Initially, only waste heat recovery was claimable for the deduction, but now co-generation in terms of combined heat and power is also claimable. A synthetic indicator at the country or industry level would not be able to capture this level of detail.

Enforcement

The stringency of environmental policies can be based on laws, regulations or directives state (de jure stringency). Firms or households subject to the regulation may however not perfectly comply with the regulation or policy (because of lack of enforcement, imperfect implementation, lack of information…), resulting in a gap between the de jure and the de facto policy stringency. This gap can vary across countries, time, sector, type of regulation and depend on other policy choices, such as the budget and capacity of enforcement agencies.

Source: Adapted from Brunel and Levinson (2013[58]).

The number of policies implemented in a given year (or their stock) has been used as an indicator of policy stringency (Le Quéré et al., 2019[59]; Eskander and Fankhauser, 2020[60]). To refine the analysis and obtain a comparison of policies, they can be further classified by sector (e.g. industry, buildings, transport etc.) and mitigation area (e.g., energy efficiency, renewables, fuel switch etc.). Nascimiento et al. (2021[61]) and D'Arcangelo et al. (2022[3]) provide taxonomies that can guide the classification.

Composite indices, such as the OECD Environmental Policy Stringency indicator (Botta and Koźluk, 2014[62]; Kruse et al., 2022[63]) can also be used to assess the effects of more stringent environmental policies on carbon emissions (Box 13). Composite indices select a number of policies and assign weights to each of them, thus providing a more detailed description of overall environmental legislative settings than employing the mere number of policies. They are especially useful for ranking countries *de jure* stringency levels. However, they are sensitive to the process of selecting and scoring policies, deciding on the aggregation structure and relative weights. The main assumptions underlying composite indices are that sub-indicators are exhaustive proxies of mitigation approaches, affect emissions homogeneously across countries and that the chosen weights approximate well the relative importance of policies.

Box 13. Regression-based approach using the OECD composite EPS indicator

The OECD Environmental Policy Stringency (EPS) aggregates 13 environmental policy instruments (focussing on climate change and air pollution regulation) into a composite index measuring the stringency of countries environmental policies, across 40 countries over three decades (1990–2020). Built in 2014 by (Botta and Koźluk, 2014[64]) and updated in 2022 by (Kruse et al., 2022[65]), the index has been used extensively in empirical studies to assess cross-country impacts of stricter environmental policies on environmental and economic outcomes and helped improve the understanding of the environmental and economic impacts of environmental policies (OECD, 2021[54]; Albrizio, Koźluk and Zipperer, 2017[66]). Using country- and sector-level data, the EPS can be used to empirically estimate the impacts of changes in countries' environmental policy stringency on countries' emissions. Using an empirical specification building upon the work of Rajan and Zingales (1998[67]) the analysis estimates the impact of Environmental Policy Stringency on emissions using sectoral-fuel intensities as a measure of exposure to the environmental regulation.

$$\ln(y_{cs,t}) = \sum_{k=0}^{10} \beta_k EPS_{c,t-k} + \sum_{k=0}^{10} \theta_k (EPS_{c,t-k} \times \bar{S}_{cs}) + +Controls + \alpha_{cs} + \delta_t + \varepsilon_{cs,t}$$

where

- $y_{cs,t}$ is the outcome variable (CO_2 emissions) in country *c,* sector *s* at year *t*.
- $EPS_{c,t}$ is the Environmental Policy Stringency Index.
- $\bar{S}_{cs}$ is the average share of fossil fuels in energy use, computed across country-sector combinations for the full sample.
- α_{cs} are country-sector fixed effects δ_t are year fixed effects.
- $Controls$ are the country-level control variables: real GDP, as well linear country-year and sector-year time-trends.
- Specifically, the yearly horizons considered are $\mathrm{k} = 0,\ 1{,}2 \ldots 10$ years.

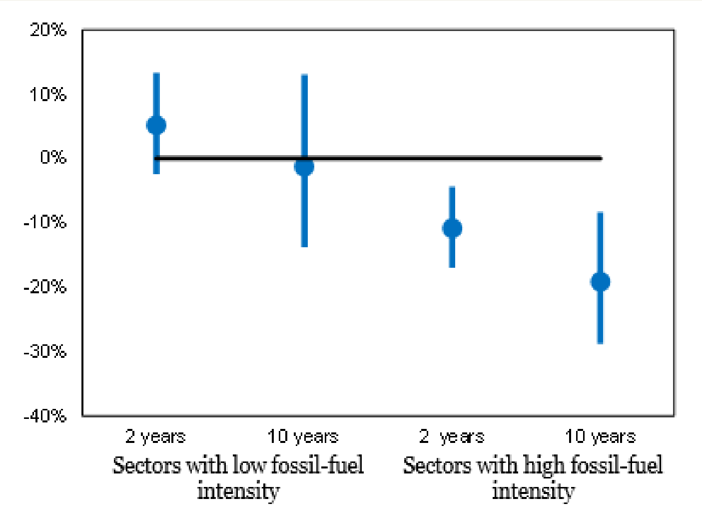
Combining data from the WIOD Socio-Economic Accounts (SEA) with the Environmental Accounts, the final dataset consists of 23 700 country-sector observations across 54 sectors in 30 OECD countries covering the years 2 000-14, which is the latest publicly available data. Data for South Africa is not included in the WIOD Socio-Economic Accounts.

The average effects across all countries in sectors with low fossil-fuel intensity is much smaller than from for sectors with high fossil-fuel intensity, both over 2- and 10-year time horizons (Figure 6). A one unit increase in the EPS (roughly equal to one standard deviation of the EPS) is associated with a reduction in emissions of approximately 10%. The effects are heterogeneous by country, reflecting differences in their industrial composition (Figure 7). A one-unit increase in EPS is associated with a nearly 10% decrease in emissions in Greece and Poland over a two-year period. Using sector-level fossil fuel intensities allows for disaggregating the effects by sector, showing that in Poland and Greece the reductions mostly come from the power sector that is relatively carbon intensive in both countries. A one unit increase in the EPS is a relatively large increase in policy stringency, approximately equal to one standard deviation of the index. For comparison, an introduction of a carbon tax and price increase from 0 to 50 USD/tCO_2 increases the EPS by 0.33 points.

Using a rich set of fixed effects and time-trends, the analysis accounts for country-sector specific time-invariant factors, for example geographical factors such as access to the sea or proximity to major markets. It also controls (with time-fixed effects) for global shocks such as the Global Financial Crisis that affected emissions and production across countries. By adding country-year and sector-year time trends it controls for country- and sector-specific changes over time, for example gradual shifts from manufacturing to service-based economies that have been observed across many OECD economies.

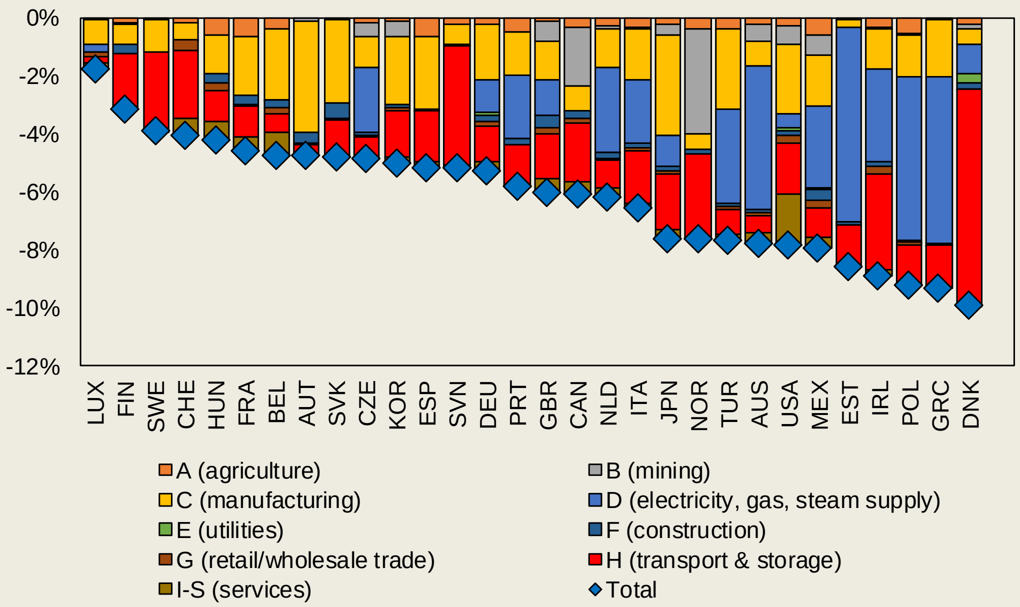
Figure 6. The effect of Environmental Policy Stringency across countries

Average effect on CO_2 emissions



Note: The figure shows the cumulative impact of a one-unit increase in EPS on CO_2 emissions for sectors with low fossil-fuel intensity and high fossil fuel intensity cumulative over a 2- and 10- year time period.
Source: Frohm et al., (forthcoming[68])

Figure 7. The effect of an increase in Environmental Policy Stringency on emissions – country-by-country effects



Note: The figure shows the cumulative effect over two years of increasing the environmental policy stringency by one unit on emissions by country and sector.
Source: Frohm et al., (forthcoming[68])

Machine learning techniques can overcome some shortcomings of using simpler measures to approximate mitigation policy stringency. While complexity reduction is judgment-driven when using the number of policy or composite indicators, machine learning adopts a data-driven approach. Machine learning implements algorithms that extract the most relevant information from the data and select a subset of relevant policy variables (or 'features'). They are otherwise similar to the other methods based on indices, in that they employ a similar cross-country regression framework. Ang, Röttgers and Burli (2017[69]) adopt one such approach to explain how climate change mitigation policies affect investment and innovation in renewable power. They collect data on more than 70 explanatory variable and employ the least absolute shrinkage and selection operator (LASSO) by Tibshirani (1996[70]) to focus on only the empirically important ones. Zachmann et al. (2014[71]) study how R&D and public deployment policies affect patenting in renewable energy, using LASSO to reduce the complexity of analysing a large set of variables emerging from lagging and interacting policy variables. Other data-driven methodology exist, differing in the underlying algorithm and more or less suited to specific applications: ridge regressions and elastic nets, regression trees and forests, deep learning and neural nets and boosting (Athey and Imbens, 2019[72]).

Cross-country approaches based on a comparison of emission trajectories

A simple way of assessing the stringency of climate policies involves comparing emissions trajectories across countries. Young (2022[53]) puts this approach forwards in the context of the proposed European Union Carbon Border Adjustment Mechanism (CBAM) by analysing countries' emission paths since the signing of the Paris Agreement. In this framework (for which the European Union is the reference region), countries that reduced emissions by less than the European Union since the Paris Agreement are considered to have a lower policy ambition, whereas countries that reduced emissions by more have a higher level of ambition. While this approach is simple and has a low data requirement it does not take into consideration countries' industrial structure and does not explicitly model the role of policies. Countries can reduce their emissions for a variety of reasons, including not only climate policies but also a shift in production patterns from manufacturing to services, which are less emission intensive. The choice of the base year to be set at the time of signing the Paris Agreement may also disadvantage countries that have made significant emission reductions in previous years. For these countries additional abatement may be more difficult to achieve because they require emission reductions in hard-to-abate sectors (for example steel or cement).Brunel and Levinson (2013[58]) developed a similar but alternative approach, which explicitly take into account countries' different sectoral structures. This approach also has low data requirements and benchmarks each country against a baseline created by predicting the emissions produced if the country had industry-level emission intensity equal to the average across other countries (Brunel and Levinson, 2013[58]). As environmental taxes and regulations raise the cost of emissions, either putting a price on emissions or establishing costly abatement requirements, firms will emit less. When the observed emission intensity of a country is higher than its benchmark, this approach concludes that the regulations are less stringent. When observed emissions intensity is lower than the baseline, mitigation policies must be more stringent. Compared to Young (2022[53]), Brunel and Levinson (2013[58]) take into account that industrial composition determines emissions and confounds estimates of policy effects, but provide a static comparison of countries without capturing how stringency evolves over time.

The two methods are combined and extended in Annex D, building on the benchmarking method of Brunel and Levinson (2013[58]) to show the evolution of stringency over time. The analysis shows how emission intensities have evolved for a number of OECD countries and relates these changes to more stringent mitigation policy and a 'greening' of the industrial composition. Some countries have both increased their mitigation efforts and progressively moved towards a less emitting industrial structure, while climate performance stagnated in other countries because of less ambitious policies, a slow transition towards lower-emitting industries, or both.

This novel approach can be used to implicitly account for factors that can be difficult to account for in regressions or forward-looking models and that could change over time, such as interactions of policies, imperfect enforcement and differences in policy coverage. However, it shares with the other two approaches described here the major shortcoming of being unable to take into account country-specific confounding elements other than industry structure, including differentiated energy price shocks, different technology diffusion and the behaviour of consumers.

Discussion

The number of ways to estimate emission reductions resulting from climate change mitigation policies demonstrates that the main task at hand is to identify a practical way forward, one that would consider resource intensity and availability, as well as the strengths and limitations of the chosen method (see Table 2). Moreover, this entails identifying the tools and data sources that would generate comparable results across countries and maintain a level of granularity at country and policy levels.

The adequacy of the modelling tool in assessing the effectiveness of climate policies in reducing emissions should be prioritised. Existing energy system models, discussed above, are best suited for the task because they allow the study of the impacts of price and non-price policies, while providing comparable yet country-specific estimates of policy-induced emission reductions, covering energy and end-use sectors. They abstract from the feedback between energy markets and the wider economy but maintain enough sectoral granularity to enable an assessment of a large suite of climate policies. In addition, by modelling emission reductions over longer time horizons into the future, this type of model is well suited to assess the effectiveness of currently implemented or planned climate change mitigation policies and can thus inform policymakers' understanding on whether a particular country is on track to reach its 2030 and 2050 targets.

The IEA's Global Energy and Climate model plays a central role in providing estimates for emission reductions of a wide range of policies across the world. At the same time, its findings can serve as inputs into the OECD Economics Department's long-term global model energy module to assess the impact of decarbonisation pathways on the economy, thus leveraging the existing synergies between the two organisations. There is also further scope to apply the Economics Department's expertise in empirical policy evaluation techniques using micro-data to estimate how climate policies or policy packages reduce emissions in specific countries and sectors. Empirically estimated elasticities can be fed into the IEA model to enrich the modelling structure and parameterise the model based on observed elasticities from micro-data.

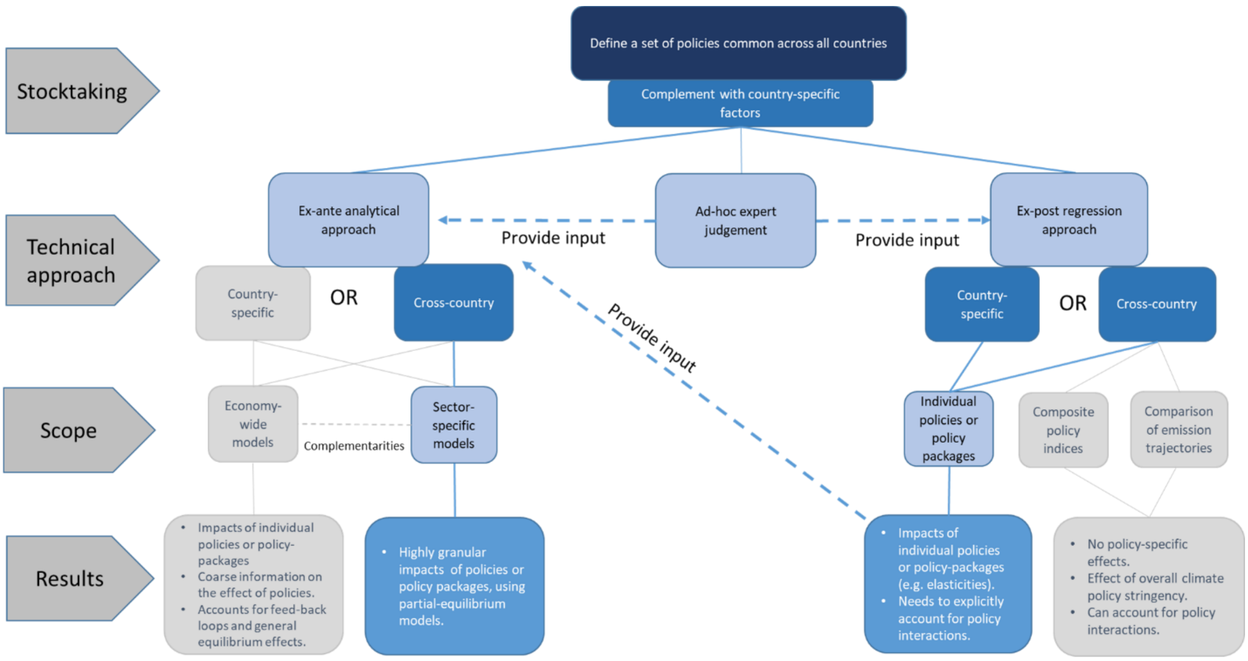
The IEA's model can be used by either taking a homogeneous cross-country perspective or a country-specific approach. The homogeneous cross-country approach focuses on collecting information on the same policy elements and evaluating their effect on emission reductions within a common framework. As such, it ensures that the same modelling framework is applied to each country. The homogeneous cross-country approach is therefore less resource intensive than the country-specific approach, which relies on tailored methodologies and on identifying relevant information and effects of polices for each country. The latter would however accommodate context-specific information that a cross-country approach may miss. Further work could be pursued in the Economics Department along the same lines as the work for WP1 on long-term carbon price elasticities (D'Arcangelo et al., 2022[52]) to provide input into existing models. Granular information on emission elasticities is required across a large number of policies and policy packages. Specifically, there is a significant gap in the literature on the responsiveness of emissions to different non-price-based instruments.

This approach is illustrated in Figure 8 highlighting in blue the preferred approach. The approach would rely on the availability of an ex-ante, cross-country, sector-specific analytical models. The IEA's Global

Energy and Climate model can provide a strong basis for this analysis covering energy end-use sectors. Other models would be needed to cover emission sources from other large emitting sectors such as agriculture, land-use change and forestry, and transport. These could include the Aglink-COSIMO model of the OECD Trade and Agriculture Directorate and Food and Agriculture Organization of the United Nations (FAO) and the transport modelling tools of the International Transport Forum. Using micro-data, the Economics Department could work closely with the IEA and other purveyors of such sector-specific ex-ante analytical models to provide empirically estimated elasticities as inputs to these models.

Outputs from the ex-ante sector-specific models could also be used in a CGE model (such as OECD ENV-Linkages) to quantify the second order effects of individual policies and policy packages on emissions. This implies the evaluation of the feedback of economic effects on emissions and thus providing a more comprehensive assessment of policy effectiveness.

Figure 8. Preferred approaches to estimate the effectiveness of climate change mitigation policies in terms of emission reductions



Note: The Figure illustrates different paths to estimate the effectiveness of climate change mitigation policies. The blue shaded boxes show the preferred approach. The grey shaded boxes show the less preferred approaches.
Source: OECD

Table 2. Characteristics of technical approaches

Technical approach	Data and model requirements	Assumptions	Advantages	Limitations
Ex-post regression of individual policies or policy packages	• Information on climate policies (type of regulation, policy design, coverage, policy exemptions etc.) and their stringency • Socio-economic control variables (country-, sector-, firm-, household-, policy-level etc.) • Data and resource requirements can vary from being moderate (using sectoral policy packages and sectoral emissions data) to high (using micro-data for specific industries, households etc.). The resource costs increase with the granularity of the policies and sectors and the robustness of the econometric analysis.	• Estimation requires exogenous variation in climate policy that causes changes in emissions • Requires the correct specification of the regression model (e.g. assuming a linear or quadratic relationship, no omitted variables etc.)	• Results are based on the empirical relationships between policies and emissions • Can estimate the effects of individual policies included in the model. • Simulations can provide forward-looking assessment of future policy changes • Future changes in policies are assumed to have similar impacts on emissions as past changes.	• No general equilibrium effects • Multiple policies and policy interactions can be difficult to estimate because of lack of sufficient variation in the data
Ex-post regression using composite policy indices	• Composite indicator of climate policy stringency • Socio-economic control variables (country-, sector-, firm-, household-, policy-level etc.). • Low to moderate data and resource requirements	• Requires exogenous variation in composite policy index that causes changes in emissions • Requires choices on how to aggregate and weigh different policies into a composite index • Requires the correct specification of the regression model (e.g. assuming a linear or quadratic relationship; no omitted variables etc.). • Changes in the policy index are difficult to relate to changes in actual policies because of weighting and aggregation.	• Accounts for interactions of policies to the extent that they are included in the composite index. • Provides the effect of a comprehensive policy package included in the composite index. • Simulations can provide forward-looking assessment of future policy changes. • Future changes in the policy stringency are assumed to have similar impacts on emissions as past changes.	• No general equilibrium effects • Cannot estimate effects of individual policies
Ex-post empirical approach focusing on comparison of emission trajectories outcomes	• Sector-level emissions and value added data across countries. • Relatively low data and resource requirements.	• Relies on the assumption that any difference between observed and predicted emissions in a country is caused by differences in policies • Requires the correct specification of the regression model to estimate the predicted emissions	• Accounts for policy interactions, including climate and non-climate policies • Relatively low data requirement • Does not provide estimates of empirical relationships between individual policies and emissions.	• No general equilibrium effects • No effects of individual policies • Does not take into account country- and time-specific determinants of emissions • All changes in emissions are attributed to changes in climate policies that may be caused by other factors (e.g. deindustrialization).
Ex-ante analytical sector-specific models	• Sector-specific partial equilibrium models with granular sector-specific data • Detailed data on the sector structure and its functioning	• Relies on the assumption that the models capture in detail the functioning of each sector • The sector is assumed to operate independently from	• Can provide the effects of policy- or policy-packages depending on the granularity of the model.	• Interactions and feedbacks between sectors may not be modelled, including upstream and downstream

	• Resource requirements depend on the availability of a suitable model. If existing models can be used the resource requirements are moderate to calibrate and adjust the model. If the model needs to be newly built the resource costs are high.	other sectors in the economy without interactions or feedbacks	• High level of detail in modelling sector- specific effects • Can incorporate detail information on abatement costs	linkages across sectors • No general equilibrium effects
Ex-ante analytical economy-wide models	• General equilibrium model with economy-wide data • Data on the economy, including sectoral relationships (e.g. input-output tables, social account matrixes) for parameterization and model calibration. • Resource requirements depend on the availability of a suitable model. If existing models can be used the resource requirements are moderate to calibrate and adjust the model. If the model needs to be newly built the resource costs are high.	• Relies on the assumption that the model captures the functioning of the economy's general equilibrium considering the relationship among several markets	• Can provide the effects of policy- or policy-packages depending on the granularity of the model. • Accounts for general equilibrium effects, including for interactions between sectors (e.g. upstream and downstream linkages across sectors; movement of production factors across sectors etc.)	• Provides an economy-wide long-run estimates with limited sectoral granularity, using a complete but simplified structure of the economy • Limitations in dealing with dynamics and market frictions

Note: This table summarizes for each technical approach the data and model requirements, assumptions, advantages and limitations.
Source: OECD.

Annex A. General considerations: country examples

This section describes and expands on the content of the "General considerations" section by providing country examples on: i) climate policies across different levels of jurisdictions, ii) the treatment of overlapping policies, and iii) the establishment of baselines for computing emission reductions. It covers examples from the United States, India, Canada, Germany, South Africa and the Netherlands.

Climate policies across different levels of jurisdictions

Several counties and states in the United States have adopted a wide range of policies to address climate change, which are generally more demanding than those hitherto implemented at the federal level. The biennial report submitted to the UNFCCC highlights the centrality of subnational climate actions in reducing GHG emissions (United States, 7th National Communication, 2020[73]). These include the development of clean energy resources, promoting alternative fuel vehicles and more energy-efficient buildings and appliances. Twenty-four states and the District of Columbia have adopted specific GHG emission targets. Carbon pricing is currently only implemented through cap-and-trade programs across participating states, and carbon taxes are being considered in a few states as well. The eleven states in the Regional Greenhouse Gas Initiative (RGGI) have implemented cap-and-trade in the power sector. California's cap-and-trade program covers nearly its entire economy and is linked with the Canadian province of Quebec. Massachusetts has two separate cap-and-trade programs to reduce GHG emissions in the power sector: it participates in RGGI and has a separate program (Reducing CO2 Emissions from Electricity Generating Facilities) that runs in parallel to RGGI. Washington state's cap-and-invest legislation will take effect beginning in 2023. Non-price-based measures are also widespread across subnational jurisdictions. Thirty state, territories and the District of Columbia have renewable portfolio standards (National Conference of State Legislatures, 2022[74]). Fifteen states, making up about 30 per cent of Unites States auto sales, currently follow at least some of California's vehicle emissions standards (Center for Climate and Energy Solutions, 2022[75]).

India is a federal country where the central government has relatively strong fiscal powers and bureaucratic capabilities. In addition, the federal government sets the agenda in many realms of climate policy. Reflecting this, India's biennial report on climate change submitted to the UNFCCC largely captures climate targets and measures undertaken at a national rather than sub-national level (MoEFCC, 2021[76]). The central government delegates the implementation of Indian climate policy to subnational governments (states and cities) and non-state (e.g. companies) actors, for instance, by tasking subnational actors to develop state-specific action plans. Non-state action is generally more prominent than sub-national governments' action, although both are still relatively underdeveloped compared with national policy action. Quantifiable emissions reduction commitments by individual non-state and subnational actors in India cover less than 10% of India's 2016 total emissions, and of these individual actors, companies make up the largest share (Lütkehermöller, Smit and Kuramochi, 2021[77]). Overall, contrary to the United States, India's federal government, rather than subnational governments, is responsible for the bulk of climate change policies and action.

The Pan-Canadian Framework, Canada's national climate plan adopted in 2016, outlines joint and individual commitments by federal, provincial and territorial levels of government (Canada, Environment and Climate Change Canada, 2016[78]). As such, in its UNFCCC annual biennial report, the Canadian government accounts for its climate change mitigation policies across all levels of government (Canada, Environment and Climate Change Canada, 2019[79]). The report focuses on key climate-related actions taken by provinces and territories, which are responsible for the majority of policy instruments aimed at reducing greenhouse gas emissions, including carbon pricing. A form of carbon pricing applies across the country using a benchmark approach. Starting in 2018, provinces and territories have been required to adopt their own carbon pricing schemes, which may include a carbon tax, a cap-and-trade system, credit trading programs for big emitters or a hybrid strategy. The federal authorities must judge these carbon pricing schemes to be comparable to the established national benchmark. For cap-and-trade systems, for example, the benchmark requires, firstly, a 2030 emissions reduction target equal to or greater than Canada's 30% reduction target; and secondly, progressively more stringent annual emission caps until 2022. For any jurisdiction that lacks a system aligned with the benchmark, a federal carbon pricing backstop applies in the form of a fuel charge (OECD, 2017[80]; OECD, 2021[81]). In sum, Canada's way of accounting for climate policies across different levels of government – federal *and* provincial – seems to lie between those of the US, which is primarily focused on subnational policies, and India, focused more on policies at the national level.

Germany's federal governance structure and vertical division of powers ensure that climate change mitigation is, to a large extent, integrated into federal and *Länder* legal frameworks. Most climate-related policies are adopted at the federal level, while the *Länder* are responsible for policy implementation. Länder ensure that any local policies adhere to federal laws and standards. To date, there are no national legal provisions in place that oblige local governments to put in place specific climate change plans and measures, nor are there any reporting mechanisms obliging municipalities to report their climate actions to the national or *Länder* governments. Still, 10 out of 16 *Länder* have put in place their own locally-binding climate change regulations in addition to federal ones (e.g., for construction and housing, energy production, transport) and most have adopted climate change-related strategies along with funding instruments for local governments. As policy implementation mainly lies with *Länder* and local governments, the national legal framework clearly shapes subnational energy and climate actions (e.g. , the energy saving act, the federal building code, etc.). (Climate Chance, 2021[82]).

South Africa implements its climate change mitigation policies at a national, rather than subnational level. The government sets sectoral and cross-sectoral regulatory (legislation, regulations and standards) and economic (incentives and taxes) policies to reduce emissions across the economy, while provincial and local governments are responsible for integrating climate change action into their strategies and plans under the guidance of the Department of Forestry, Fisheries and the Environment (DFFE). Seven of the nine provinces have announced their green economic or climate change plans, ranging from energy efficiency measures to adaptation and development of renewable energy (Government of South Africa, 2014[83]). However, provincial and regional governments' strategies are typically not binding. In this context, the analysis of climate change mitigation policies might focus only on policies implemented at a national level (such as carbon tax, environmental levies, tax incentives).

The treatment of overlapping climate policies

The Netherlands estimates the impacts of the main policy packages on the reduction of GHG emissions by sector and greenhouse gas. Hence, the government measures the effects of policy instruments on climate change by analysing policy packages affecting different sectors rather than examining individual measures. In the analyses performed at a fairly high level of aggregation for the biennial report (The Netherlands. Ministry of Economic Affairs and Climate Policy, 2018[84]), the Dutch government chooses not to distinguish the impacts of individual instruments and programmes focusing on the same emission source or activity. Doing so, it largely avoids the risk of double counting.

South Africa primarily maps its climate policies onto four key sectors: energy (incl. transport and manufacturing), industrial process and product use (IPPU), agriculture, forestry and other land use (AFOLU) and waste. For instance, some of the major policies attributable to the energy sector, the largest contributor to South Africa's total emissions (80.1% in 2017), include the Integrated Resource Plan, Eskom integrated demand management (IDM) programme and the 12L energy efficiency savings tax incentive that aim to diversify South Africa's energy generation sources and increase the uptake of low carbon technologies. Transport-related environmental taxation and fiscal policy instruments include fuel and vehicle levies, with the cross-sectoral carbon tax incorporated as an add-on.

Establishing a baseline against which to compare future GHG emissions

No standard practice exists in establishing baselines for computing the effect of climate change mitigation (and other) policies. In the AR6 report, the IPCC (IPCC, 2022[18]) constructs baselines on what it assumes to be current-policy scenarios in the period of 2015-2019. Typical baselines are the Shared Socioeconomic Pathway 2 (SSP2) (Fricko et al., 2017[85]) and the Current Policies scenarios from the World Energy Outlook 2019 (IEA, 2019[27]), which contain median expectations of population growth and economic development. For instance, for the energy sector, the potentials were determined using the World Energy Outlook 2019 Current Policies Scenario as a reference, in which energy demand rises by 1.3% each year to 2040. Variations of up to 10% between the different baseline scenarios exist with respect to macro-variables such as total primary energy use as well as total GHG emissions (IEA, 2019[27]).

South Africa's biennial update report highlights the country's "peak, plateau and decline (PPD)" GHG emissions trajectory, which is a projection of emissions with a starting point in 2016 (Marquard et al., 2021[86]). The PPD trajectory projects emissions by 2025 and 2030 to be in a range of between 398 and 614 Mt CO_2–eq. Key drivers of GHG emissions in the modelling framework used to determine the PPD trajectory are GDP growth and population. The trajectory of future emissions up to 2030 was modelled based on two different economic growth rates: a reference growth rate reaching 2.4% by 2030, and a high growth rate reaching over 4% by 2030.

The Climate Act released by the Dutch government in 2019 sets a goal to reduce greenhouse gas emissions by 49% before 2030 compared to 1990. The PBL has drawn up a baseline scenario assessing the potential of implemented and planned policies (as of May 2021) to reduce emissions in line with this target by 2030, as well as further progress to be achieved by 2040 towards the country becoming carbon-neutral. In doing so, it bases its analysis on the anticipated development of key exogenous factors, such as economic growth, demographic changes, fuel and CO_2 prices and technological progress.

Annex B. Sectoral details of the IEA Global Energy and Climate Model

The IEA Global Energy and Climate Model incorporates multiple sectoral modules that quantify the effects on energy demand and CO2 emissions from the power sector, and five major end-use sectors: industry, buildings and services, transport, agriculture, and non-energy use of energy commodities.

The power sector module includes data on the existing quantity and type (coal, oil, gas, nuclear, hydro, bioenergy, solar PV, wind, or other renewables) of power generation capacity and assumptions on planned changes (new additions or plant retirements) to meet electricity and heat demand. Information on countries' electricity market design, including the competition structure, and market reliability are incorporated, allowing for modelling the effects of policy changes on energy-demand and energy-related emissions.

The industry sector module contains detailed data at the sectoral level, especially for the most energy-intensive sectors, namely aluminium, steel, chemicals, cement and paper production. Information on end-use energy prices, type of fuel use, historic production and economic growth and population growth feeds into the module to determine energy supply, demand and CO2 emissions from industrial processes. The module also assesses the impact of policies on heat supply for industrial purposes, separately by temperature level, showing that the amount of heat required by industrial processes and fuel use changes substantially across policy scenarios.

Using socio-economic and historic inputs (population, rate of urbanisation, electrification rate, GDP, building stock, new constructions, energy balances etc.), the IEA's buildings sector model assesses trends and the effects of policy scenarios on structural demand drivers (e.g. household occupancy, residential floor area, appliances ownership, etc.) and energy demand (space and water heating, cooking, lighting, etc.) to model final energy demand, CO2 emissions and investments in the building sector.

The IEA's transport demand module distinguishes between road and non-road transport. Road transport is split into passenger and freight transport, with the freight module building upon projections of freight transport, separately for each type of freight transport type (light-duty, medium-duty, heavy-duty trucks). It uses granular information from Electronic Diesel Control (EDC) systems used in trucks for metering diesel consumption to model changes in transport-related energy demand and CO2 emissions. Detailed econometric modelling is used to model effects in the aviation, rail and shipping sector.

Annex C. Types of policies covered across CGE models

Table A C.1. CGEs cover non-price-based policies to varying degrees

	AIM - Hub	DART	GEM-E3	GRACE	ICES	IMACLIM	MESSAGE-GLOBIOM	SNOW GL HH	WEGDYN	WITCH
Emission tax	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑
Emission pricing	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑
Cap and trade	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑
Fuel taxes	☑		☑	☑	☑	☑		☑	☑	☑
Fuel subsidies	☑		☑	☑	☑	☑		☑	☑	☑
Feed-in-tariff			☑	☑					☑	
Portfolio standard	☑		☑				☑		☑	
Capacity targets	☑		☑	☑		☑	☑		☑	☑
Emissions standards	☑			☑		☑	☑	☑	☑	☑
Energy efficiency standards	☑			☑		☑	☑		☑	
Agricultural producer subsidies	☑			☑					☑	
Agricultural consumer subsidies	☑			☑					☑	
Land protections	☑									

Note: This table lists only those models that are classified as CGE models in the IAMC documentation. Those policies in bold are non-price-based climate policies.
Source: The common Integrated Assessment Model (IAM) documentation - IAMC wiki.

Annex D. Empirical evidence on mitigation policy stringency based on emission trajectories

The method of Young (2022[53]), based on benchmarking emission trends in countries to a certain reference year, and that of Brunel and Levinson (2013[58]), based on benchmarking emissions from countries at a given time adjusting for their industry composition (Box A.D.1) can be combined to provide a fuller picture. Moreover, the same principles can be employed to create an index of industrial structure 'greenness' to disentangle the nature and channels through which emission intensities have changed over time.

Box A D.1. Empirical methodology based on Brunel and Levinson (2013)

Brunel and Levinson (2013[58]) define E_c and V_c to be total emissions and value added in country *c*, summed across all industries. They define:

$$e_c = \frac{E_c}{V_c} \quad (1)$$

to be emissions per dollar of value added in country *c*, averaged across all industries (Eq. 1), and define e_s to be the emissions per dollar of value added in sector *s*, averaged across all countries (Eq. 2).

$$e_s = \frac{E_s}{V_s} \quad (2)$$

Where E_s and V_s are total emissions and value added in industry s, summed across all countries. Then $\hat{e}_c$ are the *predicted* emissions per dollar of value added in country *c*, assuming each of its industries uses the average emissions intensity for all countries.

$$\hat{e}_c = \frac{1}{V_c} \sum_s V_{sc} e_s \quad (3)$$

This is a prediction of country *c*'s emissions intensity based solely on its industrial compositions (the V_{sc}'s) and the average emissions intensities of those industries in other countries. If a country has a lot of high-emitting industries, we would expect it to have a high value of $\hat{e}_c$. If its mix of industries is relatively clean, we would expect a low $\hat{e}_c$.

The *actual* emissions intensity of a country is equivalent to a weighted average of the actual emissions per dollar of value added of each industry in that country (e_{sc}) where the weights are the industries' shares of total output in that country (V_{sc}/ V_c). The *predicted* emissions intensity of a country is a weighted average of the national average emissions per dollar of value added in each industry (e_s), where the weights are the same (V_{sc}/V_c).

One measure of the stringency of regulations, R_c, is the ratio of predicted emissions intensity to actual emissions intensity:

$$R_c = \frac{\hat{e}_c}{e_c} \quad (4)$$

Countries that impose higher pollution abatement costs on their industries will have smaller-than-predicted emissions, and higher levels of Rj, no matter their industrial composition. This measure could also be constructed on an annual basis to observe changes over time.

This approach requires data on value added by industry and country, and the emissions in each country (which does not need to be sector-specific), and the total amount of emissions by each sector (which does not need to be country-specific). The emissions data however need to be limited to the industries covered in the index (Equation 4). For example, in the absence of information on value added of the transportation or household sector, these sectors should also not be part of the emissions data.

For example, a country A produces all its value added from basic metal manufacturing with a carbon intensity of 4000 tonnes of CO_2 per million USD, while country B produces all its value added from basic metal manufacturing with a carbon intensity of 1000 tonnes of CO_2 per million USD. If on average across all countries the carbon intensity of basic metal production were 2000 tonnes of CO_2 per million USD value added, country A's regulatory stringency in basic metal manufacturing is (expressed as the ratio of the predicted to the observed emissions intensity) is 0.5 (2000/4000 = 0.5), and country B's regulatory stringency is 2 (2000/1000 = 2).

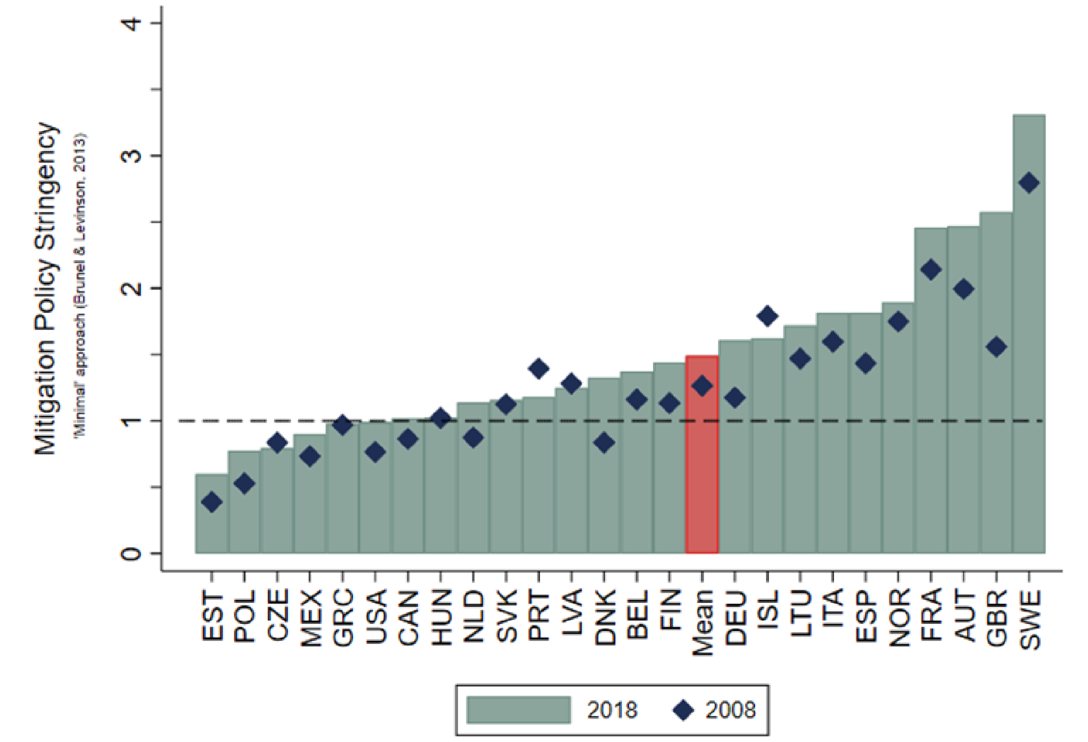
Note: This box describes the methodological approach outlined in Brunel and Levinson (2013[58]).
Source: (Brunel and Levinson, 2013[58])

The approach of Brunel and Levinson (2013[58]) is further refined to show the evolution of stringency over time, by constructing 'baseline' emissions from industry-level emission intensity averaged over time, in addition to over countries (Figure A D.1). Wide heterogeneity persists across countries, suggesting that several countries have large margins to improve their climate performance. While most countries have improved their emission intensities in the decade from 2008 to 2018, few still lag far behind and the improvements have been insufficient to bring them at comparable levels with the others.

Figure D.2 further builds on Brunel and Levinson (2013[58]) to show an index capturing how emissions vary across economies based on their industrial structure ('Greenness of industry structure'). The baseline of each country is computed by multiplying the value added from a benchmark country with average industry structure by actual industry emission intensities. The ratio of these predicted emissions to the observed ones gives indication of the reliance of the economy on low-carbon industries. An index above one means that the country would increase its emissions, at current emission intensities, if it had an average industry structure.

Changes in the industry structure also reflect changes in mitigation policies. Mitigation policies tend to favour low-emission industries and technolgies at the expenses of high-emitting ones. Possibly for this reason, actvitiy in many of the countries in Figure A D.2 have progressively shifted towards less emitting industries, although volatility in the underlining data on value added do not allow for a clear-cut interpretation. These changes have not necessarily led to lower global emissions as a shift away from high emitting industries in some countries is more than offset by an increase of production and emissions in other countries with laxer mitigation policies (i.e. 'carbon leakage').

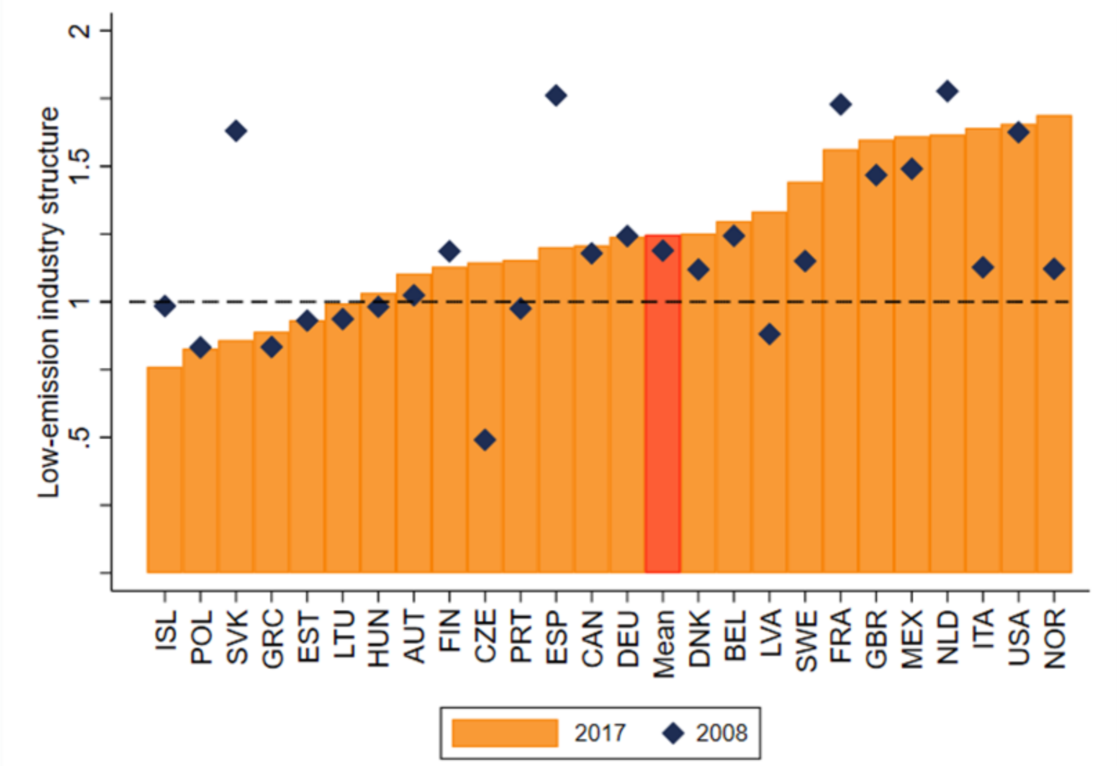
Figure A D.1. Mitigation policy stringency accounting for countries' industry strucure differ measured from observed emissions



Note: Higher values imply higher mitigation policy stringency. A value below 1 means that, with the same industry structure, a country would reduce its emissions if its sectors' emission intensity was equal to the cross-countri average for that sector (average taken across countries in the years 2000 – 2018).
Source: OECD.

Figure A D.3 shows the mitigation policy stringency indicator of Brunel and Levinson on the y-axis and the index on the greenness of the industry structure. In the bottom-left quadrant, polluting industries account for a large share of the economy and mitigation policy stringency is low. These countries tend to have the highest emission intensity at aggregate level. Thus, they have much potential to reduce emissions from shifting economic activity towards cleaner industries (i.e. sectors with low emission intensity) and reducing the emissions intensity of sectors though more stringent mitigation policies. Countries in the top-right quadrant are the opposite. Their economies consist of sectors with low emission intensity and economic activity is tilted towards less emitting sectors. In the top-left quadrant, countries exhibit a low emission intensity compared to their peers, reflecting stringent mitigation policy, but high emitting sectors account for a larger share of total production than the average country. These countries have more room than the average country to reduce emissions by shifting economic activity towards low emitting sectors than further raising mitigation policy stringency (which is already stringent compared to the average). The bottom-right quadrant contains countries with a greener industrial structure (i.e. low-emitting sectors accoun for a larger share of economci activity) but less stringent mitigation policies than the average country. In other words, despite an economy focused on lower emitting industries, emission intensities are relatively high in those industries compared to the average. These countries have scope to reduce emission by ramping up mitigation policies.

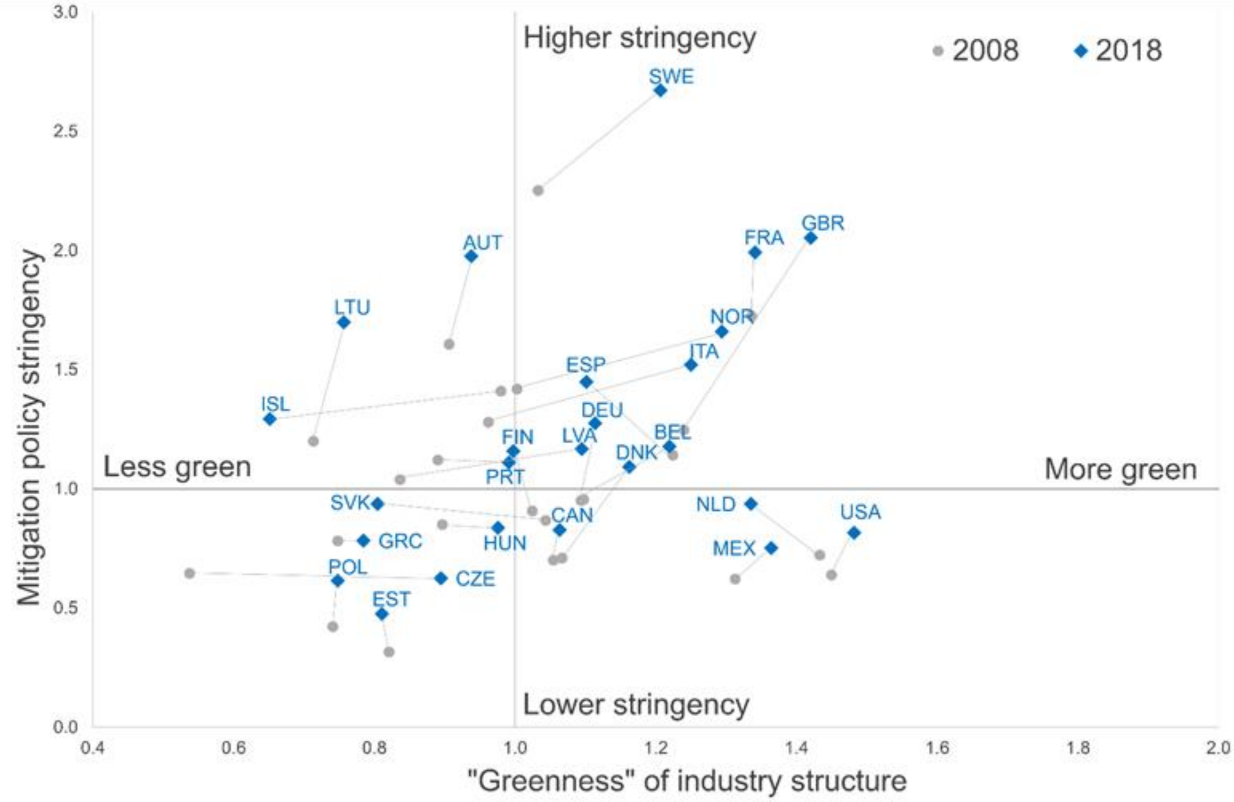
Figure A D.2. Emission intensity of industry structure measured from observed emissions



Note: Higher values imply that a larger share of value added produced in the economy comes from industries with low emission intensity. A value below 1 means that, with the same sectors' emission intensity, the country would reduce its emissions if it had the same industry structure as the average country (average taken across countries in the years 2000 – 2017).
Source: OECD.

The stringency measure of Brunel and Levinson correlates with the OECD Environmental Policy Stringency (Kruse et al., 2022[63]) obtained aggregating selected mitigation policy indicators in a composite index (Figure A D.4). The correlation coefficient is 0.39 in 2018 and 0.24 in the 2000 – 2018 period. This shows that this indicator based on outcomes captures underlying changes in mitigation policies. However, not every change in policy translates in contemporaneous lower emissions with respect to the baseline (only 14% of the variation in the outcome indicator is explained by variation in the EPS, as measured by the R^2 of a linear regression of the former on the latter). One explanation is that some policies, such as those that support innovation in green technologies, take time to reduce emissions. Another explanation is that emission fluctuations are caused by other elements than those captured by the indicators in the EPS index.

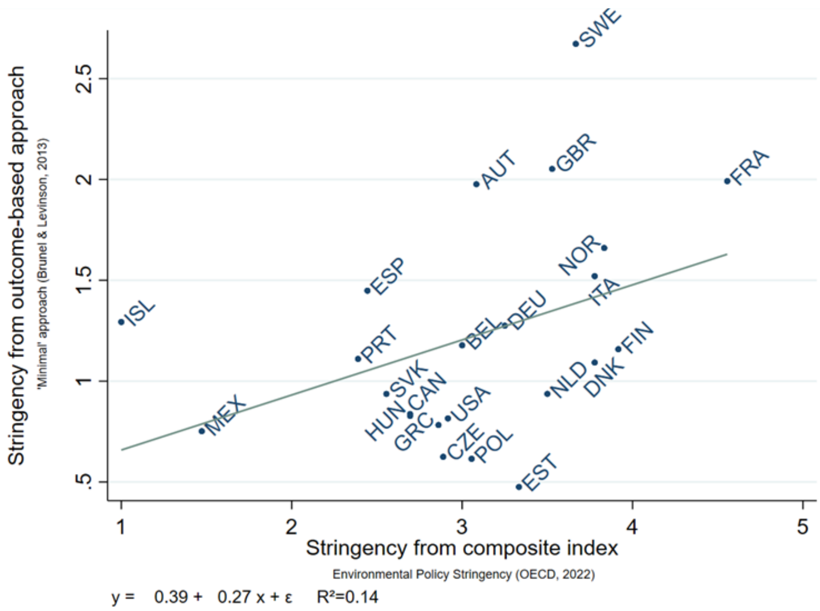
Figure A D.3. Relationship between countries mitigation policy stringency and the greenness of their industry structure



Note: Mitigation Policy Stringency (y-axis) is calculated following the 'minimal' approach of Brunel and Levinson (2013[58]). Greenness of industry structure (x-axis) is calculated as the ratio of predicted emissions, obtained by multiplying the value added from a benchmark country with average industry structure by observed industry emission intensities, and observed emissions. A country with 'greener' industry structure is a country with a larger share of value added produced in industries with lower emission intensity.
Source: OECD.

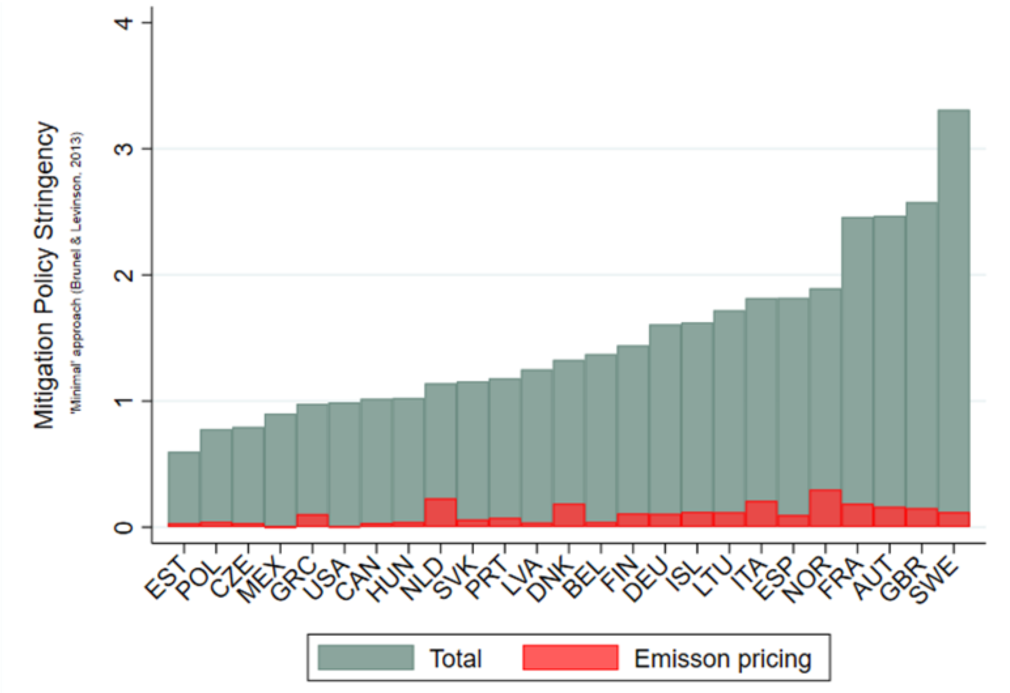
Figure A D.5 relates outcome-based mitigation policy stringency with data on emission pricing and exemplifies how the analysis based on outcomes (emissions) can be enriched with results from external cross-country regression studies. Higher red bars show that emission pricing contributes more to mitigation policy stringency by lowering emission intensity with respect to the benchmark. They are calculated employing data and results from D'Arcangelo et al. (2022[52]), which estimates the emission elasticity to pricing and taxes, collected in a homogeneous and comparable measure, the Effective Carbon Rates (OECD, 2021[1]).

Figure A D.4. Outcome-based and composite indices measures of policy stringency are correlated



Note: Data refer to 2018
Source: OECD.

Figure A D.5. Emission pricing still contributes little to performance improvements



Note: Mitigation policy stringency computed with the method of Brunel and Levinson (2013[58]) is further divided to reflect the contribution of emission pricing (red bars). The grey bars capture non-pricing policies, as well as structural differences in emission intensities other than industry structure, which is accounted for. The red bars are calculated estimating the differential emissions in absence of pricing by country and accordingly recalculating equation (4). The differential emissions are obtained employing the estimated average semi-elasticities of emissions to pricing contained in D'Arcangelo et al. (2022[52]) and data on Effective Carbon Rates (ECR) by country. The ECR is computed as an emission-weighted average, excluding the road transport sector, which is not relevant for the sectors considered in the analysis.
Source: OECD.

References

Abrell, J., M. Kosch and S. Rausch (2022), "How effective is carbon pricing? A machine learning approach to policy evaluation", *Journal of Environmental Economics and Management*, Vol. 112, https://doi.org/10.1016/j.jeem.2021.102589. [14]

Albrizio, S., T. Koźluk and V. Zipperer (2017), "Environmental policies and productivity growth: Evidence across industries and firms", *Journal of Environmental Econonics and Management*, Vol. 81, pp. 209-226. [66]

Alton, T. et al. (2014), "Introducing carbon taxes in South Africa", *Applied Energy*, Vol. 116, pp. 344-354, https://doi.org/10.1016/j.apenergy.2013.11.034. [43]

Andersson, J. (2019), "Carbon Taxes and CO2 Emissions: Sweden as a Case Study", *American Economic Journal: Economic Policy*, Vol. 11/4, pp. 1-30. [12]

Andor, M., A. Gerster and J. Peters (2022), "Information campaigns for residential energy conservation", *European Economic Review*, Vol. 144, https://doi.org/10.1016/j.euroecorev.2022.104094. [17]

Ang, G., D. Röttgers and P. Burli (2017), "The empirics of enabling investment and innovation in renewable energy", *OECD Environment Working Papers*, No. 123, OECD Publishing, Paris, https://dx.doi.org/10.1787/67d221b8-en. [69]

Annicchiarico, B. and F. Di Dio (2015), "Environmental policy and macroeconomic dynamic in a new Keynesian model", *Journal of Environmental Economics and Management*, Vol. 69, pp. 1-21, https://doi.org/10.1016/j.jeem.2014.10.002. [46]

Athey, S. and G. Imbens (2019), "Machine Learning Methods That Economists Should Know About", *Annual Review of Economics*, Vol. 11/1, pp. 685-725, https://doi.org/10.1146/annurev-economics-080217-053433. [72]

Berestycki, C. et al. (2022), "Measuring and Assessing the Effects of Climate Policy Uncertainty", *OECD Economics Department Working Papers No. 1724*. [89]

Blok, K. et al. (2020), "Assessment of Sectoral Greenhouse Gas Emission Reduction Potentials for 2030", *Energies*, Vol. 13/4, p. 943, https://doi.org/10.3390/en13040943. [88]

Botta, E. and T. Koźluk (2014), "Measuring environmental policy stringency in OECD countries", *Economics Department Working Papers*, No. 1177, OECD, Paris, https://doi.org/10.1787/5jxrjnc45gvg-en (accessed on 17 January 2019). [64]

Botta, E. and T. Koźluk (2014), "Measuring Environmental Policy Stringency in OECD Countries: A Composite Index Approach", *OECD Economics Department Working Papers*, No. 1177, OECD Publishing, Paris, https://dx.doi.org/10.1787/5jxrjnc45gvg-en. [62]

Brucal, A. and A. Dechezleprêtre (2021), "Assessing the impact of energy prices on plant-level environmental and economic performance: Evidence from Indonesian manufacturers", *OECD Environment Working Papers, No. 170*, https://doi.org/10.1787/9ec54222-en. [57]

Brunel, C. and E. Levinson (2013), *Measuring Environmental Regulatory Stringency*, https://doi.org/10.1787/5k41t69f6f6d-en. [58]

Canada, Environment and Climate Change Canada (2019), *Canada's 4th Biennial Report to the United Nations Framework Convention on Climate Change*, Environment and Climate Change Canada. [79]

Canada, Environment and Climate Change Canada (2016), *Pan-Canadian Framework on Clean Growth and Climate Change : Canada's plan to address climate change and grow the economy*, Gatineau, Quebec : Environment and Climate Change Canada, 2016. [78]

Center for Climate and Energy Solutions (2022), *Federal Vehicle Standards*, https://www.c2es.org/content/regulating-transportation-sector-carbon-emissions/. [75]

Château, J., R. Dellink and E. Lanzi (2014), "An Overview of the OECD ENV-Linkages Model: Version 3", *OECD Environment Working Papers*, No. 65, OECD Publishing, Paris, https://dx.doi.org/10.1787/5jz2qck2b2vd-en. [38]

Chateau, R., R. Dellink and E. Lanzi (2014), "An Overview of the OECD ENV-Linkages Model", *OECD Environment Working Papers*, Vol. 65, https://doi.org/10.1787/5jz2qck2b2vd-en. [23]

Chen, W. et al. (2007), "Carbon emission control strategies for China: A comparative study with partial and general equilibrium versions of the China MARKAL model", *Energy*, Vol. 32, pp. 59-72. [31]

Climate Chance (2021), "Germany - Case study on multi-level climate governance", https://www.climate-chance.org/wp-content/uploads/2021/03/germany-climate-governance-climate-chance-2.pdf. [82]

Cohen, M. and M. Vanderbergh (2012), "The potential role of carbon labeling in a green economy", *Energy Economics*, Vol. 34/1, pp. S53-S63, https://doi.org/10.1016/j.eneco.2012.08.032. [16]

D'Arcangelo, F. et al. (2022), "A framework to decarbonise the economy", *OECD Economic Policy Papers*, No. 31, OECD Publishing, Paris, https://dx.doi.org/10.1787/4e4d973d-en. [3]

D'Arcangelo, F. et al. (2022), *Estimating the CO2 emission and revenue effects of carbon pricing: new evidence from a large cross-country dataset*, OECD Publishing, Paris. [52]

de Mello, L. and J. Martinez-Vazquez (2022), "Climate Change Implications for the Public Finances and Fiscal Policy: An Agenda for Future Research and Filling the Gaps in Scholarly Work", *Economics*, Vol. 16/1, pp. 194-198, https://doi.org/10.1515/econ-2022-0026. [10]

Dechezleprêtre, A., D. Nachtigall and F. Venmans (2018), "The joint impact of the European Union emissions trading system on carbon emissions and economic performance", *OECD Economics Department Working Papers*, No. 1515, OECD Publishing, Paris, https://dx.doi.org/10.1787/4819b016-en. [13]

DFFE (2021), *South Africa'S 4th Biennial Update Report To The United Nations Framework Convention On Climate Change*, Department of Forestry. Fisheries and the Environment. Republic of South Africa. [7]

Dussaux, D. (2020), "The joint effects of energy prices and carbon taxes on environmental and economic performance: Evidence from the French manufacturing sector", *OECD Environment Working Paper* No. 154, https://doi.org/10.1787/b84b1b7d-en. [19]

Energy Innovation (2022), *Comparing the Energy Policy Simulator to Other Energy and Climate Models*, https://energyinnovation.org/wp-content/uploads/2022/05/Energy-Policy-Simulator-Model-Comparison.pdf. [34]

Eskander, S. and S. Fankhauser (2020), "Reduction in greenhouse gas emissions from national climate legislation", *Nature Climate Change*, Vol. 10/8, pp. 750-756, https://doi.org/10.1038/s41558-020-0831-z. [60]

Evans, J. and L. Hunt (eds.) (2009), *Bottom-up Models of Energy: Across the Spectrum*, Edward Elgar Publishing Limited. [26]

EZK (2019), *The Netherlands Fourth Biennial Report Under the United Nations Framework Convention On Climate Change*, Ministry of Economic Affairs and Climate Policy (EZK) Directorate General for Climate Change and Energy. [21]

Fricko, O. et al. (2017), "The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century", *Global Environmental Change*, Vol. 42, pp. 251-267, https://doi.org/10.1016/j.gloenvcha.2016.06.004. [85]

Frohm, E. et al. (forthcoming), "Estimating Emissions Reductions from Changes in Environmental Policy - An Application using Sector- and Country-level Data", *OECD Economics Department Working Paper*. [68]

Galeotti, M., S. Salini and E. Verdolini (2020), "Measuring environmental policy stringency: Approaches, validity, and impact on environmental innovation and energy efficiency", *Energy Policy*, Vol. 136, https://doi.org/10.1016/j.enpol.2019.111052. [22]

Gambhir, A. et al. (2019), "A Review of Criticisms of Integrated Assessment Models and Proposed Approaches to Address These, through the Lens of BECCS", *Energies*, Vol. 12/9, https://doi.org/10.3390/en12091747. [49]

Gielen, D. et al. (2001), "Biomass for energy or materials?: A Western European systems engineering perspective", *Energy Policy*, Vol. 29/4, pp. 291-302, https://doi.org/10.1016/S0301-4215(00)00123-3. [32]

Government of South Africa (2014), *National Climate Change Response. White Paper*, https://www.gov.za/sites/default/files/gcis_document/201409/nationalclimatechangeresponsewhitepaper0.pdf. [83]

IEA (2022), *Global Methane Tracker 2022*, https://www.iea.org/reports/global-methane-tracker-2022. [30]

IEA (2021), *World Energy Model Documentation*, https://iea.blob.core.windows.net/assets/932ea201-0972-4231-8d81-356300e9fc43/WEM_Documentation_WEO2021.pdf. [24]

IEA (2019), *World Energy Outlook*, https://www.iea.org/reports/world-energy-outlook-2019. [27]

IMF/OECD (2022), *Delivering Climate Mitigation under Diverse National Policy Approaches*. [2]

IPCC (2022), *Chapter 12: Cross sectoral perspectives*, https://report.ipcc.ch/ar6wg3/pdf/IPCC_AR6_WGIII_FinalDraft_Chapter12.pdf. [28]

IPCC (2022), *Chapter 12: Cross sectoral perspectives*, https://report.ipcc.ch/ar6wg3/pdf/IPCC_AR6_WGIII_FinalDraft_Chapter12.pdf. [90]

IPCC (2022), *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, https://www.ipcc.ch/report/ar6/wg2/about/how-to-cite-this-report/. [18]

Kiuila, O. and T. Rutherford (2013), "The cost of reducing CO2 emissions: Integrating abatement technologies into economic modeling", *Ecological Economics*, Vol. 87, pp. 62-71, https://doi.org/10.1016/j.ecolecon.2012.12.006. [35]

Kruse, T. et al. (2022), *Measuring environmental policy stringency in OECD countries: An update of the OECD composite EPS indicator*, https://doi.org/10.1787/90ab82e8-en. [65]

Kruse, T. et al. (2022), "Measuring environmental policy stringency in OECD countries: An update of the OECD composite EPS indicator", *OECD Economics Department Working Papers*, No. 1703, OECD Publishing, Paris, https://dx.doi.org/10.1787/90ab82e8-en. [63]

Le Quéré, C. et al. (2019), "Drivers of declining CO2 emissions in 18 developed economies", *Nature Climate Change*, Vol. 9/3, pp. 213-217, https://doi.org/10.1038/s41558-019-0419-7. [59]

Lohmann, P. et al. (2022), “Do carbon footprint labels promote climatarian diets? Evidence from a large-scale field experiment”, *Journal of Environmental Economics and Management*, Vol. 114, https://doi.org/10.1016/j.jeem.2022.102693. [15]

Lütkehermöller, K., S. Smit and T. Kuramochi (2021), *Non-state and subnational climate action in India. An overview of the current landscape, emission reduction potential and implementation*, NewClimate Institute. [77]

Marquard, A. et al. (2021), *Technical Analysis to support the update of South Africa’s First NDC’s mitigation target ranges (UCT 2021)*, University of Cape Town. Report, https://doi.org/10.25375/uct.16691950.v2. [86]

MoEFCC (2021), *India: Third Biennial Update Report to the United Nations*, Ministry of Environment, Forest and Climate. [76]

Nascimento, L. et al. (2021), “Twenty years of climate policy: G20 coverage and gaps”, *Climate Policy*, Vol. 22/2, pp. 158-174, https://doi.org/10.1080/14693062.2021.1993776. [61]

National Conference of State Legislatures (2022), *State Renewable Porfolio Goals and Standards*, https://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx#:~:text=Renewable%20Portfolio%20Standards%20(RPS)%20require,production%20and%20encourage%20economic%20development. [74]

Nikas, A., H. Doukas and A. Papandreou (2019), “A Detailed Overview and Consistent Classification of Climate-Economy Models”, *Understanding Risks and Uncertainties in Energy and Climate Policy*. [25]

Nordhaus, W. and Z. Yang (1996), “A Regional Dynamic General-Equilibrium Model of Alternative Climate-Change Strategies”, *The American Economic Review*, Vol. 86/4, pp. 741-65, http://www.jstor.org/stable/2118303. [48]

OECD (2022), *Global Plastics Outlook: Economic Drivers, Environmental Impacts and Policy Options*, https://doi.org/10.1787/de747aef-en. [40]

OECD (2022), *Stocktaking and mapping of price-based climate change mitigation policies*. [11]

OECD (2021), *Assessing the Economic Impacts of Environmental Policies: Evidence from a Decade of OECD Research*, OECD Publishing, Paris., https://doi.org/10.1787/bf2fb156-en. [54]

OECD (2021), “Carbon Pricing in Times of COVID-19: Key Findings for South Africa”, https://www.oecd.org/tax/tax-policy/carbon-pricing-south-africa.pdf. [6]

OECD (2021), *Effective Carbon Rates 2021: Pricing Carbon Emissions through Taxes and Emissions Trading*, OECD Publishing, Paris, https://dx.doi.org/10.1787/0e8e24f5-en. [1]

OECD (2021), *Integrating Environmental and Climate Action into Development Co-operation: Reporting on DAC Members’ High-Level Meeting Commitments*, OECD Publishing, Paris, https://dx.doi.org/10.1787/285905b2-en. [39]

OECD (2021), *OECD Economic Surveys: Canada 2021*, OECD Publishing, Paris, https://dx.doi.org/10.1787/16e4abc0-en. [81]

OECD (2019), *Taxing Energy Use 2019: Using Taxes for Climate Action*, https://doi.org/10.1787/058ca239-en. [87]

OECD (2017), *OECD Environmental Performance Reviews: Canada 2017*, OECD Environmental Performance Reviews, OECD Publishing, Paris, https://dx.doi.org/10.1787/9789264279612-en. [80]

OECD (2016), *Effective Carbon Rates: Pricing CO2 through Taxes and Emissions Trading Systems*, https://doi.org/10.1787/9789264260115-en. [91]

OECD (2016), *The Economic Consequences of Outdoor Air Pollution*, https://doi.org/10.1787/9789264257474-en. [41]

Partnership for Market Readiness (2016), *Modeling the Impact on South Africa's Economy of Introducing a Carbon Tax*, World Bank, Washington, DC. © World Bank, https://openknowledge.worldbank.org/handle/10986/25762. [45]

Pauw, K. (2007), *Economy-wide Modeling: An input into the Long Term Mitigation Scenarios process*, https://open.uct.ac.za/bitstream/item/19436/Pauw_Economy_wide_Modeling_An_2007.pdf?sequence=1. [42]

PBL (2021), *IMAGE (Integrated Model to Assess the Global Environment)*, https://models.pbl.nl/image/index.php/IMAGE_framework. [51]

PBL (2016), *Kostenefficiëntie van beleidsmaatregelen ter vermindering van broeikasgasemissies*, https://www.pbl.nl/sites/default/files/downloads/pbl-2016-kostenefficientie-van-beleidsmaatregelen-ter-vermindering-van-broeikasgasemissies_1748.pdf. [20]

Petrick, S. and U. Wagner (2014), "The impact of carbon trading on industry: Evidence from German manufacturing (RMS)", *Kiel Working Paper*, Vol. No. 1912, https://www.econstor.eu/handle/10419/94357. [55]

Pindyck, R. (2017), "The Use and Misuse of Models for Climate Policy", *Review of Environmental Economics and Policy*, Vol. 11/1, pp. 100-114. [50]

Pörtner, H. et al. (eds.) (2022), *Terrestrial and Freshwater Ecosystems and Their Services*, Cambridge University Press, Cambridge. [9]

Rajan, R. and L. Zingales (1998), "Financial Dependence and Growth", *The American Economic Review*, Vol. 88/3, pp. 559-586, https://www.jstor.org/stable/116849?seq=1#metadata_info_tab_contents. [67]

Rivera, G. et al. (2017), "The State of Applied Environmental Macroeconomics", *Revue de l'OFCE*. [36]

RIVM (2021), *Greenhouse gas emissions in the Netherlands 1990–2019 National Inventory Report 2021*, https://unfccc.int/documents/273459. [8]

Sue Wing, I. and E. Lanzi (2014), "Integrated Assessment of Climate Change Impacts: Conceptual Frameworks, Modelling Approaches and Research Needs", *OECD Environment Working Papers*, No. 66, OECD Publishing, Paris, https://dx.doi.org/10.1787/5jz2qcjsrvzx-en. [37]

The Netherlands. Ministry of Economic Affairs and Climate Policy (2018), *The Netherlands Fourth Biennial Report Under the United Nations Framework Under the United Nations Framework*, https://unfccc.int/sites/default/files/resource/NLD%204th%20Biennial%20Report%20Final%20version%2018dec19.pdf. [84]

Tibshirani, R. (1996), "Regression Shrinkage and Selection Via the Lasso", *Journal of the Royal Statistical Society: Series B (Methodological)*, Vol. 58/1, pp. 267-288, https://doi.org/10.1111/j.2517-6161.1996.tb02080.x. [70]

UNEP, UNEP-CCC (2020), *Emissions Gap Report 2020*, https://www.unep.org/emissions-gap-report-2020. [29]

United States, 7th National Communication (2020), *A Review of Sustained Climate Action through 2020*. [73]

US EPA (2022), *Global Warming Potential*, https://www.epa.gov/ghgemissions/understanding-global-warming-potentials. [4]

Van Heerden, J. et al. (2016), "The economic and environmental effects of a carbon tax in South Africa: A dynamic CGE modelling approach", *South African Journal of Economic and Management Sciences*, Vol. 19/5, pp. 714-732, https://doi.org/10.4102/sajems.v19i5.1586. [44]

Varga, J., W. Roeger and J. in 't Veld (2021), "E-Quest - A Multi-Region Sectoral Dynamic General Equilibrium Model with Energy", *European Commission Discussion Paper No. 146*. [47]

Wagner, U. et al. (2014), "The Causal Effects of the European Union Emissions Trading Scheme: Evidence from French Manufacturing Plants", *Working Paper*, http://conference.iza.org/conference_files/EnvEmpl2014/martin_r7617.pdf. [56]

Winkler, H., A. Hughes and M. Haw (2009), "Technology learning for renewable energy: Implications for South Africa's long-term mitigation scenarios", *Energy Policy*, Vol. 37/11, pp. 4987-4996, https://doi.org/10.1016/j.enpol.2009.06.062. [33]

World Resources Institute (2022), *Climate Watch Historical GHG Emissions*, https://www.climatewatchdata.org/ghg-emissions. [5]

Young, M. (2022), "Improving border adjustment mechanisms", *University of Adelaide Working Paper 09*, https://iit.adelaide.edu.au/ua/media/1873/iit-wp09-final-24052022-1.pdf. [53]

Zachmann, G., A. Serwaah-Panin and M. Peruzzi (2014), "When and How to Support Renewables?—Letting the Data Speak", in *Green Energy and Efficiency, Green Energy and Technology*, Springer International Publishing, Cham, https://doi.org/10.1007/978-3-319-03632-8_12. [71]