STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
5350 Thesis in Economics
Academic year 2018-2019

Carbon tax for emission targets

An alternative application of the DSGE model for optimal fossil fuel taxation by Golosov, Hassler, Krusell and Tsyvinski 2014

Anita Hafner (41063)

Abstract
Economists widely agree that a Pigouvian fee on emissions is the first best option to correct for the un-priced externality of climate change. However, scientific estimates of future global costs of climate change are varying. So are estimates of future carbon uptake and climate forcing as well as the estimated probability, timing and size of tipping points. Integrated assessment models are highly sensitive to these parameters and as a result are limited in their ability to precisely derive optimal policy choice. This study discusses the impact of multiple uncertainties in policy optimisation models on climate mitigation policy choice and suggests an alternative approach to IAM policy optimization, introducing an exogenous emission target in the place of carbon uptake and damage functions. This approach shifts model dependency on unknown parameters of the climate function to a dependency on parameters that are more frequently discussed in the policy context. Drawing from the general closed economy setting of Golosov et al, a fossil energy tax formula is developed that demonstrates that the optimal tax rate given a dynamic emissions target can be expressed as a function of the target, energy intensity of the economy, technology levels of the energy sectors, and substitutability of energy inputs, among others.

Keywords: Carbon tax, IAM, damage function, economic policy, emission targets
JEL: H23, Q2, Q3

Supervisor: Chloé le Coq
Date submitted: May 13, 2019
Date examined: May 28, 2019
Discussant: Kseniia Gunko
Examiner: Mark Sanctuary

Acknowledgements

Thank you Sara, Peter, Caroline and Christina for handing me a problem that I cannot let go of anymore. Thank you to everyone at SSE for providing an excellent, fun, challenging and inspiring study environment at all times.

Contents

List of Figures

List of Tables

List of Abbreviations

ABM	Agent-based model
BAU	Business as usual
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
DSGE	Dynamic stochastic general equilibrium
ECS	Equilibrium climate sensitivity
ETS	Emissions trading system
ESM	Earth system model
GDP	Gross domestic product
GHG	Greenhouse gas
GHKT	Golosov, Hassler, Krusell and Tsyvinsky, authors of [40]
Gt	Gigaton
GWP	Global warming potential
IAM	Integrated assessment model
IPCC	The Intergovernmental Panel on Climate Change
NDC	Nationally determined contribution
MAC	Marginal abatement cost
PA	Paris Agreement
POM	Policy optimisation model
PEM	Policy evaluation model
SCC	Social cost of carbon
TCR	Transient climate response
UNFCCC	United Nations Framework Convention on Climate Change

1. Introduction

Warming of global climate is unequivocal, and there is scientific consensus it is anthropologically caused. Scholars can explain mechanisms of atmospheric greenhouse gas (GHG) uptake with increasing detail, and there is good evidence for quantifying lifespans of different greenhouse gases and their radiative effects. There is understanding for patterns of past climates, and there are improving estimates of how different levels of climate change will impact our planet over time. While these estimates vary, they all call for direct and targeted action at a global scale. The 2016 ratified Paris Agreement aims to raise global ambitions, and parties to the agreement have submitted Nationally Determined Contributions (NDCs) as voluntary, self-determined targets for national emissions levels in 2030 and beyond. As of now, there is no enforcement mechanism in place and it is left to national governments to take action.

There exists a range of suitable policies that governments can implement in order to achieve emissions reductions on the national level. The IPCC, among others, classified the main climate change mitigation policies as economic instruments (carbon pricing schemes, subsidies, related border tax adjustments), regulatory approaches (regulations and standards), information policies, government provision of public goods and services (R&D support, infrastructure, management of public goods such as forests and oceans) and facilitation of voluntary action [27]. Due to varying local circumstances, objectives and constraints, optimal policy choice and alignment of policies varies across countries, and tailored policy packages are necessary [2].[1] Nevertheless, there is strong consent among policy experts that carbon pricing mechanisms need to be at the core of all climate policy packages to achieve significant reductions while minimizing total welfare cost [57].[2] Economists widely agree that a Pigouvian price on greenhouse gas emissions is the first best policy option to address the related externality.

Carbon pricing mechanisms can take various forms and can apply to all or only selected greenhouse gases. Common approaches can be classified as either emissions trading schemes (ETS) or carbon taxes, but hybrid forms exist.[3] Both types have similarities as well as distinct advantages and climate policy instrument choice is subject to substantial economic

[1]This is the case only where other market imperfections limit the policy instrument and pareto optimal conditions will not be obtained ("second-best theory"). Many economists have called for caution when applying a mix of policy instruments as a first-best response (see for example Fankhauser et al 2010 [53] and Lehmann and Gawel 2013 [30])

[2]Climate policy commonly refers to policy for climate change mitigation and climate adaptation. The focus here is on the former solely.

[3]An Emission trading scheme introduces a ceiling for emissions within a defined market and distributes a corresponding amount of emissions allowances to market participants. Participants can trade allowances to compensate for excessive emissions or be rewarded for additional mitigation results. A carbon tax is a monetary levy on a good based on the good's emission intensity. It may be applied at point of production or consumption. Both instruments introduce an explicit carbon price.

literature [29]. A full list of active pricing schemes can be found in the appendix.

While global coverage of GHG covered by pricing schemes is increasing, global levels of carbon taxes and average prices of emission certificates are far below what researchers suggest as social cost of carbon (SCC) and hence optimal carbon price, following Pigou [40]. Scholars have identified political economy constraints as main causes for this science policy disconnect, including distributional consequences of pricing mechanisms, lobbying pressure, international policy coordination and near-time costs to consumers [28]. Additionally, uncertainty is an important barrier to policy implementation. In contrast to other public policy domains, climate policy decisions must be made in the face of uncertainty that interacts with highly nonlinear environmental cost functions, important irreversibilities and very long time horizons [49]. One result of these key uncertainties is that policy optimization models deliver wide ranges of "optimal" future carbon levels and hence wide ranges for the optimal time path of policy interventions, leaving policy makers with unclear recommendations.

Integrated assessment models (IAMs) were developed for the purpose of quantifying the social cost of carbon, quantifying the costs of climate change mitigation and to explain how policy measure can impact different elements of the economy. Today, IAMs are mainstream instruments in climate change economics, but their use for policy optimization is heavily criticized. A famous opponent of IAMs is Robert Pindyck, who not just highlights model shortcomings, but states that these models can be "highly misleading" as they suggest an illusory level of knowledge and precision of results and he claims that "climate change policy can be better analyzed without the use of IAMs" [46].

The Paris Agreement (PA) is the most important recent milestone of the global community in uniting efforts to limit climate change in the future. It is built around a collective target of limiting climate change to well below 2 degrees Celsius above pre-industrial temperature levels, aiming for only 1.5 degrees Celsius warming (Decision 1/COP21). Importantly, member parties to the PA are required to submit Nationally Determined Contributions (NDCs). NDCs are nationally determined, voluntary commitments to an individual national mitigation target and national adaptation measures and are accessible to the public. NDCs commonly use national levels of annual greenhouse gas emissions to quantify national mitigation targets, expressed in absolute terms, as shares of historic emission levels or as improvement against some defined business-as-usual (BAU) scenario. This emissions centered approach has strongly impacted international discussion on tracking progress towards implementation of the Paris Agreement (Global Stocktake) as well as related fields such as international climate finance, national policy setting or abatement efforts of the private sector, where aggregated tons of CO_2 equivalent (CO_2e) have become the central unit for measuring outcomes. A policy focus on CO_2e outcomes has the benefit of being measurable (within limitations of accounting challenges), internationally observable and it is, indisputably, closely linked to climate outcomes.

There is and has been since decades a vivid scholarly debate on the needs for policy action [56, 60], optimal instrument choice [29, 2, 20] and, most prominently, on estimating the social cost of carbon to inform optimal policy choice given uncertainty [56, 57, 40]. There is furthermore a rich literature discussing shortcomings of climate change policy modelling approaches [47, 46, 3, 51]. Fewer work has been conducted identifying barriers to policy implementation and explaining this science policy disconnect [28, 20] or discussing the integration of targets into policy optimisation [37, 13].

This thesis analyses the existing suite of economic models for climate policy optimisation from a policy makers perspective. It summarises key shortcomings of IAMs, the class of models most frequently used for policy analysis and optimisation. It then suggests an alternative application of existing CGE modelling work that addresses some of these shortcomings, linking modelling efforts closer to the current status quo of international climate change cooperation, a debate centered on emission outcomes. Under the assumption that high uncertainty around parameters characterising the damage function and high model complexity limit the relevance of a model to policy makers, this approach aims to provide an example for a simple explanation of the impact of a carbon tax on the emissions from the energy sector of a closed economy. This thesis argues that there should be a richer set of models that explicitly aim to inform policy makers in their decisions, taking into account their need for clarity, reduced uncertainty and a focus on annual emissions as central outcome.

Following the setting of the DSGE model for optimal carbon taxes for fossil fuels of Golosov et al. 2012 [40], I demonstrate how introducing emission targets to a reduced general equilibrium setting can replace the damage function and result in a simplified but clear model for carbon taxes for emission targets. With this approach, a given target emissions pathway can be directly translated into a corresponding tax pathway over time, requiring only input of common parameters for characterising the economy such as elasticity of substitution of production parameters and fuel intensity of sectors. Other than the baseline model and other policy optimisation models, this approach therefore does not identify the optimal tax level over time but identifies the path towards any selected emissions level. While this method can be applied to other existing CGE policy optimisation models, the author is not aware of an existing similar model with this approach. Furthermore, this study as a whole aims to support voices that quest for innovative yet practical policy optimization models.

This study is structured as follows. Section 2 provides context by exploring the decision makers perspective on policy choice and the status quo in global climate policy. Section 3 provides a comprehensive background for and overview of different approaches to climate change externality modelling. It explains what the main shortcomings of latest modelling efforts are and discusses arguments of both critics and advocates. Section 4 then expands on the motivation and hypothesis of this paper. Section 5 introduces the case study, a baseline model following Golosov, Hassler, Krusell and Tsyvinski 2014, and demonstrates suggested modifications, as well as presenting details of calibration and solution method. Subsequently, section 6 presents results and discusses policy implications, limitations and the validity of this modelling approach. Section 7 concludes.

2. Background: A policy makers perspective on climate change policy setting

2.1. *National incentives*

There is a growing momentum for climate change policy uptake, and policy makers as well as the public debate make the topic of optimal instrument choice one of increasingly high importance. The toolbox of policy makers for climate mitigation policy is extensive, including economic instruments such as carbon pricing schemes and related border tax adjustments, subsidies (and fossil subsidy removal), regulatory approaches including regulations and standards, information policies, government provision of public goods and services(R&D support, infrastructure, management of public goods such as forests and oceans)and facilitation of voluntary action [27]. A policy maker evaluates the option against a large set of potentially competing evaluation criteria. Most commonly analysed are economic efficiency, defined as aggregate net benefits, cost effectiveness, distributional effects (regional, demographic, socio-economic, among others), political feasibility, political credibility (management of market expectations) and policy related risk of excessive or insufficient abatement imposing high cost on the economy, which is closely linked to uncertainty around instrument design [20]. Any evaluation of policy instruments needs to be clear about the choice of criteria against which the analysis is conducted.

Uncertainty is an unavoidable aspect of policy choice and therefore not unique to mitigation policy choice. However, climate policy decisions are made in the face of uncertainty that interacts with highly nonlinear environmental cost functions, important irreversibilities and very long time horizons [49]. It is therefore crucial to consider an instrument's robustness to various uncertainties as well as the speed at which the instrument can adjust to new information as the information becomes available. Section 3 discusses key uncertainties affecting optimal policy choice and how modelling approaches develop around these. The aspect of uncertainty around policy optimisation is central to this study and discussed in various aspects.

Following elementary economic theory, the Pigouvian principle suggests that negative externalities of pollution should be internalised by pricing pollution at its marginal cost to the economy. It follows that to achieve maximal cost-effectiveness, all agents should face an equal price on emissions. Under perfect information and fully competitive markets, carbon pricing would be the first best policy choice with regards to the decision criteria economic efficiency and cost effectiveness, and revenue spending of pricing revenues could furthermore mitigate unwanted distributional effects of the policy. Where markets are incomplete and in the presence of policy constraints, this may no longer be the case. This study focuses on policy optimisation via introduction of a carbon pricing scheme only, but acknowledges the variety of instruments and their respective implications and strengths.

Policy choice is not only a question of instrument choice, but also a question of instrument calibration. Calibration is especially key for carbon pricing schemes that require a decision on the price or total quantity of emissions in carbon tax schemes and cap and trade schemes respectively. Required inputs for both calibrations are estimates for the social cost of carbon (SCC), and in addition calibrating an ETS requires estimates for the marginal abatement cost curve of the economy.

2.2. *International climate policy context*

The climate is a global public good. According to theory, a successful international climate agreement should be based on three principles: universality (all countries and regions participate), efficiency (the reduction objective should be achieved at least cost), and equity (efforts must be shared according to a uniformly accepted principle)[15]. A uniform global carbon tax would be consistent with these three principles. However, international climate negotiations are subject to real-world constraints and an unanimous agreement of all countries seems not feasible given current negotiation outcomes.

The Paris Agreement has therefore adopted a "polycentric" approach, combining diverse, voluntary policy efforts at multiple levels and thereby overcoming the challenge of formulating a rule of "fair effort sharing". Furthermore, the polycentric approach diversifies risks related to instrument choice, as a multitude of employed instruments prevents dependence on a single instrument whose failure would have large consequences.

Part of this polycentric approach built into the PA is the requirement for parties to submit Nationally Determined Contributions (NDCs). NDCs are nationally determined, voluntary commitments to an individual national mitigation target and national adaptation measures. NDCs are accessible to the public and progress against the specified targets can be tracked, but there are no formal enforcement mechanisms in place. Most NDCs refer to national levels of annual greenhouse gas emissions in order to quantify national mitigation targets, expressed in absolute terms, as shares of historic emission levels or as improvement against some defined BAU scenario.

While this international policy focus on CO_2e outcomes has the benefit of being observable to a certain degree and is closely linked to climate outcomes, it comes along with significant challenges of accountability of emissions [22]. When discussing emissions levels as a central outcome of climate policy, it is necessary to note that there are significant challenges and disputes around the topic of consistent and comparable accounting that require careful design of standards and ongoing updates.

2.3. *Status quo*

As of 2018, 88 parties to the Paris Agreement have indicated in their NDC that they are planning or considering to implement carbon pricing as an instrument to meet their nationally determined target [7]. In 2018, the total value of implemented pricing schemes globally was USD 82 billion, 56% above the market size of 2017. 47 national and sub-national carbon pricing initiatives were implemented end of 2018, covering 14% of global annual GHG emissions. If all pricing schemes that are scheduled come into implementation, this share could reach over 20% of global annual GHG emissions, covered by 51 initiatives by 2020.[4] Especially Asia and the Americas have recently seen the introduction of a number of initiatives.

Prices in implemented explicit carbon pricing initiatives vary between below USD 1 per ton CO_2e to USD 139 CO_2e. However, less than 25% of emissions covered by pricing schemes are priced above USD 12. A price below this threshold can be considered too low for the policy to effectively support low carbon transition efforts of covered sectors. Carbon pricing schemes are frequently implemented incorporating phased approaches. This is to allow for adjustments to the system design, infrastructure development and piloting phases.

In summary, there is continued progress on carbon pricing, and initiatives are covering parts of all world regions. Despite large additions to the number of pricing schemes in recent years, global coverage of GHG emissions remains low. In addition, the majority of carbon pricing schemes prices carbon at a cost that is assessed as too low to be effective by experts [39]. Table 5 in the appendix provides a long list of carbon pricing schemes that are currently active or near implementation, as well as the current prices where these are available, and lists them next to the countries' NDC ambitions.

[4]Conflicting estimates of the share of global GHG emissions covered by ETS or carbon taxes exist. This paragraph draws from the State and Trends of Carbon Pricing 2018 Report, higher estimates can be found for example in the I4CE Global panorama of carbon prices 2017 [39].

3. Background: Introduction to climate change externality modelling

3.1. *Scientific consensus and uncertainties on climate forcing*

To understand the aim, challenges, and limitations of climate change externality models it is necessary to review facts and unknowns on climate change and its impact over time. The following section mainly draws from the updated version of the *2014 Climate Change Synthesis Report* of the Intergovernmental Panel on Climate Change (IPCC) [25] as well as their *2018 Special Report on the impacts of global warming of 1.5° above pre-industrial levels [...]*[26]. The IPCC is the international body for the continuous assessment of climate change, aiming to provide a clear scientific view on the current state of knowledge in climate change and its potential environmental and socio-economic impacts, reflecting the global range of views and expertise of thousands of contributing scientists.

There is clear evidence that the climate system has warmed over the last decades, and that this change has anthropogenic causes. Observed magnitude and speed of changes in atmosphere temperature, ocean temperature, polar ice sheets and sea levels are unprecedented over decades. The increase in globally averaged combined land and ocean surface temperature between 1880 and 2012 can be narrowed down to lie between 0.65°C and 1.06°C with a likelihood of 90%, and every coming decade is estimated to add between 0.1°C and 0.3°C due to past and current emissions [25, 26]. With the same confidence it can be stated that global mean sea level rose by between 0.17m and 0.21m since 1901, and that oceanic uptake of carbon dioxide (CO_2) has resulted in a 26% increase in acidity. Over 90% of the increase in energy stored in the climate system is accumulated in the oceans, and ocean warming is largest near the surface. There is mixed evidence on precipitation trends for different latitudes. Atmospheric concentrations of CO_2, methane and other greenhouse gases today are with high confidence unprecedented for at least 800 000 years. With high confidence, fossil fuel combustion and industrial processes accounted for about 78% of the total GHG emissions increases in recent decades. The IPCC Fifth Assessment Report furthermore concludes that it is *extremely likely* that this anthropogenic increase in atmospheric GHG concentrations has caused more than half of the observed warming of global surface temperatures since 1951, and it has possibly caused all observed warming over this period. It has *very likely* contributed to increases in ocean temperature and global mean sea level rise since 1970[25].

Emissions of CO_2 into the atmosphere are the strongest driver of climate change. Atmospheric CO_2 alters the energy budget of the earth, as it has the property of allowing sunlight to pass through more easily than infrared radiation, while most of the outflow of energy from earth is infrared radiation. As a consequence, heat accumulates and increases the temperature on earth, causing higher outflow of energy until a new equilibrium energy balance occurs at warmer overall temperature. Other, less prevalent greenhouse gases like methane and nitrous oxide show different levels of absorption of infrared radiation, potential indirect effects and persist for a different length of time in the atmosphere. In order to be able to compare and aggregate different greenhouse gases, CO_2 has been chosen as reference gas, with a global warming potential (GWP) normalized to one (applied to units of mass, measured over 100 years). GWP values of all known greenhouse gases are published and regularly updated by the IPCC. CO_2e, carbon dioxide equivalent, is the related metric measure. Greenhouse gases are not the only anthroprogenic climate forcers, but the most important one.

Observed climate change has already shown impacts on natural and human systems, and we can measure changes in extreme weather events. There is strong evidence of widespread impacts of climate change on wildlife, and hydrological systems are clearly affected by changing precipitation and melting ice. Impacts on human systems can also be identified, with negative impacts on crop yields as most commonly cited immediate effects. Since 1950, we observed a decrease in cold temperature extremes, and increases in high temperature extremes and incidents of strong precipitation, which all are very likely caused by human influence.

There are large unknowns concerning key drivers of future climate and characteristics of future climate system changes. Analyzing a wide range of concentration pathways and mitigation scenarios, the IPCC finds that the scenarios jointly suggest a strong, consistent and almost linear relationship between aggregated CO2 emissions and corresponding expected temperature changes over time. There is no certainty on the factor translating cumulative emissions over time to temperature pathways. "Multi-model" results are frequently used in this context, for example to define thresholds for cumulative CO_2 emissions that would limit human-induced warming to 2°C relative to pre-industrial levels with defined levels of probability. Future increases of global mean surface temperature or reductions in glaciers and permafrost will depend largely on the emissions pathway until then, but earth system models can project differences in average changes by region.

Finally, future risks, feedback effects, irreversibility and tipping points remain difficult to model. Climate change will amplify existing risks, and resulting damage on human and natural systems will depend on their ability to adapt. While we know that various tipping points exist, that are thresholds of temperature increases that would trigger sudden large and irreversible change in natural systems, the precise levels of warming that will trigger these are uncertain. Furthermore, we know that current changes in natural systems such as the loss of some ecosystems will continue even if anthropogenic CO_2 emissions and global warming were to stabilize, and most of these changes are irreversible on a multi-century time horizon. Technologies that are able to remove large amounts of CO_2 from the atmosphere could, however, possibly revert the warming trend.

The scientific community has defined 1.5°C of global warming above pre-industrial levels as ambitious target and likely threshold to more critical changes. Different pathways to achieve no overshoot of this target see global anthropogenic CO_2 emissions reach net zero between 2045 and 2055, and estimate the remaining carbon budget for this target to lie between 420 $GtCO_2$ and 770 $GtCO_2$ depending on various assumptions and chosen level of certainty to reach the target. International negotiations on climate targets will be further discussed in section 3.5.

In summary, clear upward trends in atmospheric greenhouse gas concentrations, global warming and related changes in the ecosystem can be observed. We are able to produce more precise estimates for correlations than ever before, but there are large uncertainties related to future outcomes. Table 1 provides an overview of parameters most relevant to modelling climate change, classified in 3 categories (own classification), and respective scientific certainty.

Table 1: Parameters for climate change externality modelling and uncertainty

Category	Example parameters	Level of certainty	Sources
Technological progress and feasibility	a. technological progress on carbon capture and storage & decarbonization of transport, availability of scarce natural resources for renewable energy roll out; b. feasibility of alternative, not yet existing technologies (eg solar radiation modification)	a. medium b. unknown	various
Carbon uptake and climate forcing	a. lifespan of potent greenhouse gases, relative global warming potential per gas; b. climate response to GHG emissions, non-anthropogenic GHG emissions, remaining carbon budget by target, ocean carbon cycle	a. relatively certain but can change over time; b. substantial uncertainties	EPA, IPCC
Scale and characteristics of damage from climate change	damage function over time, regional and sectoral distribution of damages, secondary effects, feedback effects, tipping points	substantial uncertainties	IPCC, various

Source: Author, based on IPCC Synthesis Reports (multiple years)

3.2. *Development and use of climate scenarios*

The research community develops and uses scenarios to understand and analyze uncertain future interactions and outcomes of complex and interlinked climate, natural and human systems. Importantly, scenarios do not try to predict the future, but the goal of working with scenarios is to understand consequences of uncertainty and to take informed decisions based on a range of possible futures [54]. As such, scenarios reflect expert judgments regarding plausible pathways. Scenario modelling only became mainstream in the early to late 1980s, when sustainable development scenarios gained wider attention (see, for example, Häferle et al. [62]). Starting in 1990, the IPCC commissioned emissions and climate scenarios as a central component of its work. Today, the broad array and large number of scenarios available allow for comprehensive multi-model assessment of climate scenarios [25]. The research community coordinates scenario and modelling efforts to a certain extent by identifying and agreeing on important characteristics of scenarios, for example the level of radiative forcing in 2100, and then producing scenarios that can be compared along these key metrics. In climate change research, especially emissions scenarios, climate scenarios, environmental scenarios and vulnerability scenarios play an important role (see, for example, [4] for details).

Scenarios of this kind are both informed by and used in Integrated Assessment Models (IAMs), which will be discussed in more detail in the following subsection. Emissions scenarios, for example, commonly use input from integrated assessment models to evaluate patterns of economic and population growth, land use change or technological progress. At the same time, some integrated assessment models will be calibrated to match emission pathways as suggested in emissions scenarios.

Over the last years and decades, scenarios have strongly contributed to our understanding of plausible climate and socio-economic futures. They also provide an important means for increasing clarity, transparency and comparability of research and aim to increase collaboration across different groups of researchers and disciplines [4]. It is of uttermost importance to interpret results from scenarios as what they are - plausible pathways - rather than mistake them for predictions. The role of scenarios in climate change policy optimization will be discussed further in the following section.

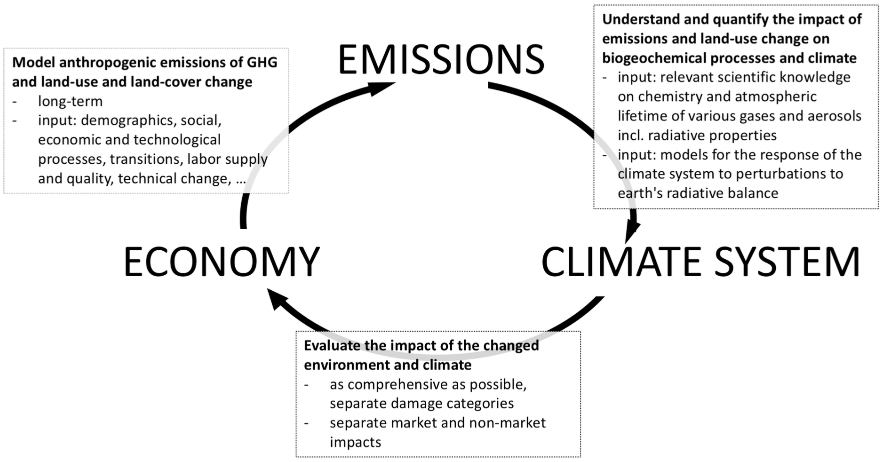
3.3. *Introduction to Integrated Assessment Models*

Modelling the economics of climate change requires a framework for simultaneously analyzing its physical and socio-economic effects over time. In addition, as N. Stern put it [56], economic analysis of climate change must be global, deal with long time horizons, incorporate the economics of risk and uncertainty and include the possibility of sudden and major change. Figure 1 provides an overview of key elements of climate change models: projections of future emissions from the economy under varying assumptions, projections of resulting atmospheric CO2e concentrations, projections of induced changes in the climate system, projections of damage (can depend on adaptation success)[14, 46].

Frameworks attempting to provide economic analysis of climate change policy, drawing from findings in multiple disciplines, are named Integrated Assessment Models.[5] In addition to the elements listed in

[5]The term Integrated Assessment Model is frequently, but not always, used in the context of environmental analysis. Nordhaus (2013) uses a more broader definition for IAMs, defining them as "approaches that integrate knowledge from two or more domains into a single framework". This discussion of IAMs relates to climate IAMs only.

Figure 1: Foundation of an integrated economic climate change model



Source: Author's depiction, based on Dowlatabadi 1995, Pindyck 2013

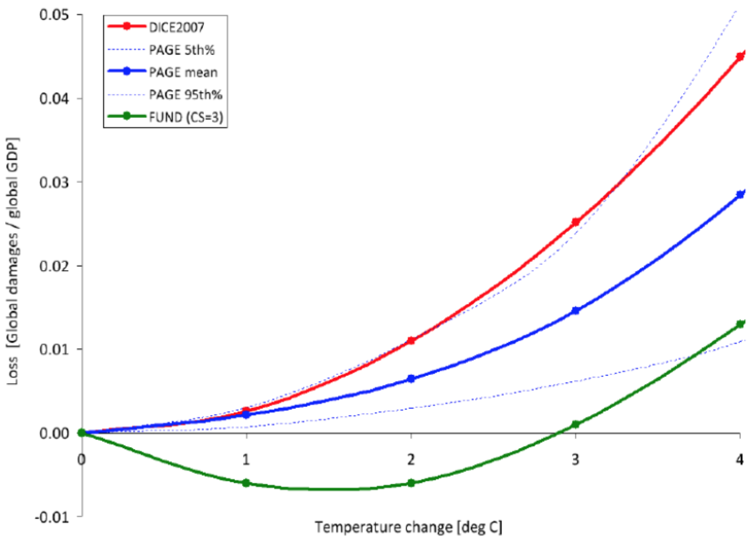
Figure 1, most IAMs include assumptions about social utility, the rate of time preference and estimates of emission abatement cost (related to projections of technical change) to be able to produce estimates of the social cost of carbon. All these inputs are modelled global or disaggregated, deterministic or stochastic and determined endogenously or exogenous. Since the first wave of IAMs in climate change analysis more than two decades ago, they are central to the scientific debate, serving as the key tool of economic assessment of climate policy around the world and forming the base of much of the work of the IPCC and its network of experts [3].

The earliest IAMs for climate change were published in the years after the newly created IPCC published its first Assessment Report in 1990 (though some earlier work may be counted, too, such as Nordhaus 1979 [42]). These pioneer models were limited by computational power and lower precision of available estimates for key parameters. They were similar in the sense that they all built on classical economic growth theory applying computable general equilibrium models (CGE) (for example DICE [43]; MERGE [34]; RICE [45]), and they had the common goal of explaining and interpreting dynamic relationships of key variables in a coherent way [3] . Some of these, most importantly DICE (Dynamic Integrated Climate and Economy, aggregated optimal growth model by Nordhaus 1994 [43]), RICE (Regional Integrated Climate and Economy, aggregated optimal growth model by Nordhaus an Yang 1996 [45]), PAGE (Policy Analysis of the Greenhouse Effect, aggregated simulation model by Hope et al. 1993 [23]) and FUND (Climate Framework for Uncertainty, Negotiation and Distribution, aggregated optimal growth model by Tol 1997 [58]) became reference models and were updated and reviewed multiple times. Today, building and using IAMs has become a "growth industry", as Pindyck describes it [46], that even has its own journal (The Integrated Assessment Journal). The IPCC, acting as a direct link between participating governments and scientists, assesses available literature on IAMs on a recurring basis and publishes summary reports.

IAMs can be built to answer different questions, and in fact there is no common overarching definition of this class of models. As they are a truly interdisciplinary class of models, with scholars from the fields of economics, engineering, sociology, biological sciences or earth sciences publishing alongside each other, there is no single aim that connects all IAMs. The 3rd Assessment Report of the IPCC [24] in 2001 provided a categorization in two subcategories: policy optimization models (POMs) and policy evaluation models (PEMs), that is commonly applied since. PEMs evaluate a given policy intervention in terms of its cost-effectiveness against a mitigation target by simulation. In general, these models tend to include a high level of detail in the physical component as well as high sectoral detail. They often do not include practical limitations such as geopolitical borders. POMs, on the other hand, have originally tended to reduce the level of detail in order to be able to perform computationally challenging optimization methods. Today, computational limitations have shifted and both POMs and PEMs use varying levels of detail, but the trends remain. Related to the emergence of common standards for scenario development, the strongly growing number of IAMs - especially the number of PEMs has increased exponentially - has caused the need to adopt common standards and abatement scenarios. POMs have become standard instruments in climate policy setting and they are the primary focus of this section.

Policy optimization models include a *damage function*, which maps changes in the climate system to damages to the economy. This characteristic enables us to use POMs to estimate the social cost of CO2, the estimate that is core to climate change policy optimization. Nevertheless, damage functions are highly simplified and often do not provide sectoral detail. Note that the parameters used in damage functions are calibrated to match available estimates of economic cost of unprecedented temperature increases, for which by definition no data exists. It is not surprising but important to note that damage functions vary significantly across different POMs (see Figure 2)[17].

Figure 2: Annual GDP loss in 2100 resulting from temperature change as estimated in the three most used POMs: DICE, PAGE, FUND



Source: EPA 2010 [17]

The three POMs depicted in Figure 2 significantly differ in the scale of damage they attribute to different levels of temperature change and also provide different level of sectoral detail of the damage. FUND includes a series of sector specific, regionally weighted damage functions resulting from sea level and temperature changes. Non-market damages are translated to monetary estimates of the related welfare loss. FUND estimates overall welfare gains from temperature change of less than 3°C [58]. PAGE differentiates economic and non-economic impacts, takes into account discontinuity impacts and sets a time varying cap for total damage (maximum vulnerability of an economy). The famous DICE model builds on the Ramsey growth model, and emission concentrations are considered negative natural capital [43]. The damage function in DICE directly reduces output.

Another possible categorization of existing IAMs is between models focused on cost-benefit analysis (for example DICE, FUND, MERGE) and other IAMs with less focus on economics but a stronger emphasis for the physical processes in both the natural system and the economy [4]. The former typically strongly simplify the carbon cycle and climate system, while the latter, focusing more on physical processes, tend to have more detail in the representation of climate and carbon cycle and often even are linked with more complex earth system models. Results from detailed process IAMs can inform and calibrate the simpler benefit-cost IAMs, and also hint to shortcomings where there are discrepancies [61].

IAMs have been constructed to estimate the social cost of carbon and to evaluate abatement pathways, and they have become a well-used tool in policy evaluation and optimization. They provide large flexibility and can be strongly simplified when needed. IAMs furthermore seem to have large potential. They can be extended to model more direct climate impacts and increased sectoral detail, and increasing quality of available data will naturally increase precision of model outputs. Nevertheless, they also have severe shortcomings. Recent years have seen more critical mention than positive, and some of the harshest critiques came from modellers and users themselves [46, 55]. The following section summarizes main limitations of these models and challenges for their application.

3.4. *Challenges and critique of IAMs*

It is striking that various IAMs evaluating abatement policies are built of the same "building blocks", but come to drastically different conclusions regarding the social cost of carbon and optimal policy pathway. Two famous extremes are Nordhaus 2008 [41], suggesting only limited immediate action consistent with social cost of \$20 per ton of CO2e and Stern 2007 [56], who concluded one year earlier that the same number was as high as \$200. This discrepancy originates from a number of model limitations, of which five are discussed in this section.

There is vast literature discussing the limitations of available IAMs and calling for caution when interpreting their results. This chapter summarizes key arguments brought up by scholars, with an emphasize on how these aspects influence suitability of policy optimization IAMs for policy making in the real world.

3.4.1 *The discounted utility framework*

IAMs are derived from economic theory, where the problem of aggregating over time benefits that are arising from a set of choices of representative agents is commonly solved by the concept of *utility.* The generic framework of IAMs is to maximize the (expected) discounted utility of one or more representative agents stretching into very distant future:

$$max\ \mathbb{E} \int_0^\infty e^{-\rho t}\, U[c(t)]\ dt \tag{1}$$

where c(t) is consumption at time t, U is the utility function, determining how much utility is derived from consumption, and ρ is the rate of time preference. Evidently, the choice of discount factor directly impacts the SSC derived from any IAM in that form. Any ρ >0 implies an unequal weighing of generations, but is a necessary assumption for the integral in equation 1 to converge. Setting ρ >0.02, corresponding to an annual discount rate of nearly 2 percent or higher, on the other hand, would result in a model that does not support high or even moderate mitigation policy. There are alternative formulations of discount formulas, but they all require some subjective rate of time preference, while economists have not yet solved the paradox and fundamental empirical challenge that "plausible" parameters of such equations commonly do not match discount rates observed in the market (see, for example, Mehra and Prescott 2003 [36]).

The choice of discounting factor is a common underlying topic in political debate and plays a key role in all public investment decisions with long time horizons and non-monetary benefits. More than an economic question, choice of discount factor is a philosophical problem and not further discussed here. See [6] for a detailed summary of arguments.

3.4.2 *Modeller's choice of inputs and form*

Related to the choice of utility discounting, there is a problematic degree of freedom of the modeller in choosing the functional form of the model as well as in calibrating the model and choosing model inputs [3]. It is equally decisive what a model is build to include, and what it is built to leave out.

Take, for example, the choice between endogenous and exogenous technical change. By design, a model with exogenous hence predictable, inexorable technological change will suggest to limit early abatement action, as future emissions reductions will come at lower cost. In contrast, one that models technical progress as a function of investment level or demonstration effects may suggest drastic early policy action [1]. In addition, the rate of productivity growth strongly impacts any resulting optimal carbon tax path over time. Other modelling choices strongly affecting results are the option to include possible negative emissions in the future, speed of depreciation of capital, curvature of the utility function or the choice of (assumed future) elasticity of substitution between different energy sources. This list can be continued (see Barrage 2013 for an extensive sensitivity analysis of an exemplary IAM [8]).

As in any economic model, the modeller has to first select the model structure and simplifying assumptions he makes, before calibrating the model by selecting parameter inputs. It is needless to say that both stages are decisive for model outputs. IAMs have the characteristic of very long time horizons as well as notably strong uncertainty around key parameters, increasing the decisive effects of modellers choices. Calel and Stainforth 2017 provide a detailed comparison of physical assumptions of three influential IAMs by running each model with parameter values that reflect the physical assumptions implicit in the other models [11]. This approach disentangles effects of parameters and structure and demonstrates the importance for IAMs to include baseline assessments with standardized physical parameter values to facilitate broad comparison of results.

3.4.3 *Uncertainty*

While the debate about social discounting, choice of assumptions and parameter choice is common to economic growth models, IAMs are particular in that they all include two key and uncertain, exogenous elements: *climate sensitivity* , translating increases in CO2e concentration to temperature effects, and the *damage function*, translating temperature change to welfare losses (or gains). As discussed in section 2, there is deep uncertainty about the relevant physical mechanisms driving both effects.

The most discussed metric in this context is equilibrium climate sensitivity (ECS), defined as global mean temperature increase in new equilibrium of the climate system resulting from an anthropomorphic doubling of atmospheric CO2e concentration (see IPCC for a detailed definition [24]). Physical science literature has a strong focus on equilibrium climate sensitivity that is reflected in the design of relevant IAMs. In their latest assessment report 2014 (AR5) the IPCC has narrowed the ECS down to *likely* lie between 1.5°C -4.5°C(with a probability of >66 percent) [25]. However, this does not rule out the possibility that climate sensitivity lies dramatically higher. Complex feedback effects and tipping points causing extreme feedback have been identified to exist, but little is known about their magnitude and warming levels that will trigger major disruptions. Fat tailed probabilities cause "expectations" to be of limited informational value [3, 51]. In fact, there is little certainty regarding the upper bound of climate sensitivity. Pindyck argues that the IPCC might understate our uncertainty over climate sensitivity in their assessment [46], and other scholars even claim that climate sensitivity cannot be assessed at all [5].

The social cost of carbon (SCC) does not just depend on the equilibrium temperature response, but also on the rate of temperature change, especially in the case of high climate sensitivities. The corresponding standardized concept is called Transient Climate Response (TCR) and considers the global average temperature change that would occur at the time of doubling if CO2 levels increase by exactly 1 percent (compounded) per year until they double. This concept is related to the ECS, but by always lower - the AR5 compares a wide range of studies and assesses the TCR as *likely* to be 1°C to 2.5°C [25]. Marten 2011, among others, demonstrated that due to oversimplification of the TCR, SCC estimates of DICE, PAGE and FUND do not match SCC estimates derived using more realistic upwelling diffusion energy balance models [35].

An equally - if not more - discussed concept under high uncertainty in integrated assessment modelling is the *damage function*, discussed in the following section.

Uncertainty challenges both parts of the climate policy model, the physical systems and the (socio-)economic systems. This section and table 1 in section 2.1 have summarized uncertainties in physical systems. IAMs furthermore share uncertainties of economic growth models, first and foremost (but not exclusively) regarding technological change.

A common approach to handling uncertainty is to assign probability distributions to uncertain parameters and to then conduct Monte Carlo simulations. This is more problematic, the more unknown the correct probability distributions are, and naturally results for expected outcomes vary largely for different distributions applied (see Pindyck 2013 [46] for a demonstration of this effect).

3.4.4 *The damage function: Uncertainty, fat tails, non-monetary values and aggregation effects*

The damage function is translating temperature changes into economic cost over time. The design of the damage function is difficult for at least three reasons (based on [3, 1]):

1. Predicting the very unknown: The scale of temperature increases that IAMs are assessing is outside of historical human experience. The climate system is furthermore a nonlinear system too complex to be described by any model, making predictions on significant temperature changes necessarily indeterminate. Scholars have agreed to apply best guesses. Consensus is stronger for smaller temperature increases and for sector specific, short-term effects where literature is large and

growing, but such insights do not facilitate calibration of overarching, long-term damage functions as used within IAMs [46].

2. Pricing of non-monetary values: Evaluating the cost of future damage from changing climate - or evaluating the benefits of mitigation measures today - requires us to assign monetary value to all spheres that we expect to be impacted, such as ecosystems, human health, civil conflicts or quality of life. This dilemma affects all cost-benefit analysis, and it is especially not new to policy analysis. A multitude of approaches from different disciplines exist to come up with surrogate prices, but there is no "right answer" to the problem.

3. Aggregating inhomogenously distributed benefits and costs: Both costs and benefits of global climate change are distributed unevenly geographically and across time. FUND, among other IAMs, assumes that aggregated effects of global climate change of less than 3°C in 2100 are significantly positive (see Figure 2 above), and IAMs agree that a large share of damage from climate change will occur in the distant future. Furthermore, climate change will most drastically and most immediately affect a small percentage of global population. While some IAMs provide sector specific or regional damage functions, they all are eventually informing a single estimate for the social cost of carbon today and do not take into account equity between population groups or intergenerational fairness.

4. Including "tail risks"[6] of unknown probability and scale: Catastrophic climate outcomes are expected to occur after tipping points in temperature increases of unknown level are reached. Such catastrophic climate outcomes would severely impact GDP, yet the temperature threshold of tipping points and the scale of resulting damage are unknown [31].

In addition to these limiting factors, the design of the damage function and its interaction with the larger model is a source of debate and differences in model outcomes. Various literature has expanded on integrating unknown feedback effects and stochastic damage shocks into the model ([31]). The damage function is furthermore commonly set to affect either GDP levels or GDP growth rates or both (Pindyck 2011 [47] provides an analysis of policy implications of this functional decision).

One can state that it is easier to quantify the costs of mitigation occurring today, than to quantify the future cost of not taking mitigation action today. As a consequence, it is commonly assumed that estimates of the social cost of carbon are skewed in this regard and provide a lower bound rather than an upper bound.

3.4.5 *Appropriate use of IAMs and model transparency*

Given these modelling challenges, any IAM that explicitly estimates the SCC comes with significant limitations around the aspects listed. A key point of critique towards "traditional" IAMs is a common lack of clarity about these limits, which in consequence leads to misinterpretation or misuse of the model and its results. Any presentation of results that does not clearly highlight the model's sensitivity towards modeler's choices and uncertainty would be strongly misleading, and in this sense a misuse of the model. Therefore, communication around both the modelling process and results is a key factor ensuring appropriate use, and should be given appropriate prioritisation by modellers [38].

[6] 'Fat tails' in the extremes of probability distributions arise when probability of extreme events is higher than they would be in a normal distribution.

Early models linking findings of climate science with social welfare considerations nearly three decades ago were built at a time when developing an understanding of the key interconnections between parameters in policy choice was key to inform first policy efforts, and the argument that IAMs are valuable models to help explain the need for policy action is brought forward until today. However, policy optimisation IAMs today largely claim that their application is not limited to explanation, and that their quantitative results can inform policy decisions [40, 43, 58, 23]. Pindyck 2017 [48], among others, argues that a model that is well suited to explain interconnections in a coherent way, is not necessarily well suited for forecasting or quantitative analysis.

3.5. *A new wave of models - recent models*

The previous section provided an overview of frequently discussed limitations of IAMs. Recent models aim to present improvements in one or more of the above aspects. Three classes of recent models are discussed here, following Farmer et al and Rezai et al ([3, 52]: dynamic stochastic general equilibrium (DSGE) models, agent-based models (ABM), and models that turn to increased parsimony. The challenges that IAMs face are partly challenges that other economic modelling disciplines face similarly, so it is not surprising that novel modelling approaches developed in finance or monetary policy are being adopted in climate policy economics.

DSGE models for climate change differ from traditional IAMs in that they explicitly introduce uncertainty by adding stochastic shocks to outcomes such as output or climate damages. Frequently, these models build on existing general equilibrium based IAMs and introduce stochastic elements and Bayesian inference. In the most traditional application, a forward looking representative agent maximises expected utility over a future that includes stochastic shocks.The fact than DSGE models can draw from previous work enabled fast progress of models of this type. At the same time, the DSGE approach to modelling, as the name suggests, shares restrictive assumptions with conventional general equilibrium models, so important critique around homogeneous agents, market clearing and the concept of equilibrium, among others, continue to apply. DSGE models have been built with regional or sector level detail,and technological change can be modelled endogenously. Furthermore, the design of the utility function allows to also model more complex agent behaviour, such as loss aversion or recursive preferences [18, 10].

Agent-based models allow for a large number of heterogeneous agents and thereby produce a more differentiated characterisation of complex socio-economic systems. ABMs with growing complexity are seeing increased application across many fields of economic and financial research as computing power and numerical algorithms are developing, a necessary prerequisite for solving extensive ABMs. ABMs applied to climate change economics can produce agent specific market outcomes for a large number of agent groups with different characteristics, reflecting distributional effects of climate change and policy measures, as well as incorporating behavioural aspects including bounded rationality. Similar to DSGE models, ABMs can introduce uncertainty in the form of stochastic events to agents forward-looking utility functions. Crucially, ABMs model the behaviour of multiple heterogeneous agents in a way that does not necessarily lead to equilibrium conditions or a unique equilibrium, leaving the modeller more flexibility to include empirical detail into the model.[7] ABMs enable the user to analyze dynamics that lead to a given equilibrium, investigate how model parameters can effect changes to these and what likelihood a given outcome has. The detail in ABMs comes at the cost of high computational complexity. As a result,

[7]Frequently, DSGE models introduce assumptions specifically so that the model can be solved in closed form with the instruments currently available. See, for example GKHT 2012 (introducing limited oil reserves of a known size)[40] and Traeger 2015 (damage function follows modelling needs)[12]

on the one hand model outcomes loose the traceability and intuition that simpler IAMs provide to a non-technical audience. On the other hand, ABMs become more susceptible to flawed computation as model complexity increases exponentially.

A third trend in recent modelling approaches is a return to parsimonious models. This could be, as described by (Farmer et al. [3]) a set of "little models", that aim to explain separate insights in partial equilibrium analysis and thereby inform experts to take policy decisions. Rezai and Van der Ploeg 2016 [52] estimate the welfare loss that may arise from implementing a policy patch derived from a "simple rule" for the optimal carbon tax rather than the first-best model, which the authors define as Nordhaus' DICE. Even for extreme scenarios, Rezai and Van der Ploeg argue that these welfare losses are negligible. Pindyck takes an even more drastic point of view and argues that expert opinions should be higher valued, to avoid false reliance on model outputs and instead go back to the "plausible", expert estimates [46]. Pizer et al. [50] similarly suggest that formal external expert review should be considered for estimating the SCC, but this should be incorporated in a model-based process for finding the SCC, together with a clear plan for regular updates to the estimation strategy. Other calls for simpler models include, for example, Bijgard et al 2016 [9] and Ackerman et al 2009. [1].

In addition to these developments, there are also voices that call for closer linkages between IAMs and and complex biophysical climate models such as MAGICC-6, HadSCCCM1 or Bern2.5CC for improved characterisation of climate forcing and the carbon cycle [59]. IAMs can also integrate full earth system model (ESM) simulations to improve detail, but uncertainties of course remain.

3.6. *Contributions of IAMs*

The scientific debate on IAMs also highlights their contributions. Carbon pricing measures, may they be implemented through a carbon tax or an ETS, require the quantification of the social marginal cost of greenhouse gas emissions. Policy makers therefore ask for models that deliver a clear numerical value for the SCC and according confidence intervals. Clearly, the "true" value of the SCC is not zero, and there are benefits from producing better and better estimates for the SCC based on scientific methods available. IAMs - in a wide definition - are producing these estimates based on the best scientific inputs available.

Metcalf and Stock argue that given fundamental uncertainties around key inputs, the SCC should not be understood as one number (or range) that can be calculated, but rather as a process towards constantly improving preliminary estimates of this value [38]. The fundamental uncertainties around parameters in IAMs are unlikely to change in the near future. IAMs therefore are needed to continue to improve and to adjust to new information as it becomes available. Metcalf and Stock furthermore argue that therefore the public debate on optimal climate policy needs to be at a higher level of sophistication than other debates.

IAMs have been central to the development of official SCC ranges by the IPCC, most prominently FUND. The Assessment Reports of the IPCC in turn inform policy decisions globally. Some governments explicitly apply IAMs themselves, for example the Interagency Working Group in the United States, which used FUND, PAGE and DICE models and 3 different discount rates to arrive at it's official estimates.

It is important to highlight that the contribution of IAMs to climate change policy optimisation is of course not limited to estimating a static SSC. IAMs are used to investigate full pathways of cost-effective emission reduction, contrast and optimise instrument choice and to evaluate the economic impacts of selected policy instruments over time [59].

In summary, IAMs are not created to generate new insights on climate science, but their aim is to explain and project interactions between the economic system and our climate system. They are built to represent mean outcomes of comprehensive climate models, while exploring economic implications of these analyses. IAMs are strongly limited by large uncertainty around key inputs, as well as - related to this - their dependency on modellers choice of form and inputs. Recent developments introduce existing frameworks of ABMs and DSGE models to the setting, delivering improvements on the aspects agent heterogeneity, detail of results and treatment of uncertainty at the cost of increased model complexity and reduced transparency.

3.7. *Models for optimal carbon tax with explicit emission targets*

Cap and trade schemes by definition set the quantity of emissions that may occur on the regulated market in a given period, while a carbon tax sets the price. There is a trade off between control over either outcome, and hybrid forms exist that aim to minimise this loss of control[29]. Hybrid instruments add one or more element of a price instrument to a quantity instrument or vice versa. Cap and trade schemes with price floors and/or ceilings are the most commonly implemented example of hybrid policy.

The equivalent hybrid form of a carbon tax is a carbon tax with ex-post adjustments to attain a predefined target. Under the assumption that greater emissions certainty under a carbon tax increases it's attractiveness to policy makers, Hafstead, Metcalf and Williams 2017 [21] design a mechanism they call Tax Adjustment Mechanism for Policy Pre-Commitment ("TAMPP"). The aim is to ensure that emission reduction targets are met, at the cost of (potentially) frequent tax adjustments. The authors do not evaluate the economic efficiency of such an approach, but explain how the mechanism could achieve its aim. In it's simplest form, the mechanism consists of a time profile of tax rates, a final emissions target and intermediate benchmarks. When emissions deviate sufficiently from the benchmark at a given benchmark point in time, the tax rate is adjusted according to a pre-defined adjustment rule. The Swiss Carbon Tax Law, among others, includes a variation of a "TAMPP" mechanism, and comparable elements are frequently found in recent policy proposals [21]. However, to my knowledge research on TAMPPs has been limited to the authors named above, and no evaluations of economic efficiency or numerical simulations of such approaches have been conducted to date.

A simpler but related challenge to the design of a "TAMPP" mechanism is modelling emissions as a function of the carbon tax rate introduced. Inherently, such a link can then be used to express carbon tax as a function of a set emissions target. While most climate-economy models endogenously define the occurrence of emissions in an economy in order to conduct cost benefit analysis of mitigation and are therefore suited for this analysis, establishing a link between a set emissions level and the resulting required tax rate does not seem to be in focus of the scholarly debate.

4. Theoretical framework and hypothesis

4.1. *Integrated Assessment Models in a political context*

G. Metcalf and J. Stock 2015 argue that, from a policy setters perspective, IAMs for policy optimisation should strive for scientific credibility, public acceptance and political and legal viability [38]. No approach exists to date that fulfills all of these criteria, but improvements on one or more aspects are possible. In this sense, there are different ways to evaluate Integrated Assessment Models for climate policy optimisation. We can evaluate their accuracy in describing and quantifying linkages between policy choice and future development of the climate system and the economy. Sections 3.4 and 3.5 above provided an overview of key arguments in this debate. Another angle lies in evaluating IAMs by identifying their success in informing the broader public debate as well as national and supranational policy decisions. While IAMs have become mainstream in policy evaluation and policy optimization around the world, global levels of carbon prices are significantly below the lower end of the range of suggested social cost of carbon, also for countries with relatively ambitious mitigation targets outlined in the country NDC [7](see table 5 of the Appendix for a list of pricing schemes and respective NDC targets). From this angle, there is an argument that IAMs should aim to further improve accessibility to policy makers and a non-expert audience.

A policy maker that decides to introduce a carbon tax to the economy has several methods to choose from for assigning a value to carbon, of which setting the price for carbon equal to an estimate for the social cost of carbon, is only one. Other options are setting a price based on observations from a functional emissions trading scheme, or calculating it based on the marginal abatement costs given a certain (optimal) target level of emissions [13]. All three options require direct or indirect inputs on the social cost of carbon. Under complete information (including an ETS with an optimal level of emissions allowance) and perfect competition, the three methods arrive at the same price for carbon.[8]

In absence of these conditions, however, the three approaches suggest different results. Since uncertainty conflicts precise calculation of social cost of carbon, this value remains an estimate. The total emissions allowance within an ETS is informed the same modelling approaches, requiring inputs in both marginal abatement costs curves and the SCC. Existing ETS are furthermore designed around political considerations and operational constraints and cover only certain sectors and regions, resulting in region and sector specific carbon prices at best. In addition, the assumption of perfect competition does not necessarily hold within the ETS or the economy, adding further discrepancy between results.

The third option for setting a carbon tax is calculating it based on the marginal abatement costs given a specific (optimal) target level of emissions. For this approach to result in optimal emissions levels, the target must be set similar to the emission cap in an optimal cap and trade scheme. Again, climate-economic modelling is required to identify the optimal target level of emissions, and assumptions on marginal abatement costs are necessary to translate the target to a tax rate.[9]

[8]This is the case as in optimum, MAC=SCC. A fully comprehensive ETS covering all emissions and capped at the optimal emissions level would be in equilibrium at p=MAC, corresponding to each agent being indifferent between abating more or buying one more unit of allowance.

[9]Abatement cost are commonly defined as the additional operating cost less potential cost savings (for example, from reduced energy consumption) resulting from reducing emissions from a certain source by one unit. Abatement cost can be presented in a cost curve where the x axis represents quantity and the y axis cost of abatement, and abatement potential by activity is presented ordered by cost from very low (negative cost) to very high (see McKinsey 2007 [16]).

4.2. *Hypothesis and approach*

A multitude of constraints on climate policy design result in global levels of carbon pricing that are far below what is suggested as optimal by most models. While traditional approaches to optimal policy choice are designed to deliver Pareto optimal results based on present-valued assessment of abatement cost and benefits, real-world constraints can limit policy choice long before the Pareto optimal level [28]. Consistent with the theory of second best [32], alternative policy design approaches can bring improvements to the current, constrained status quo.

Given significant uncertainties around the social cost of carbon, and international climate negotiations that focus on emissions as key outcome on national level, I argue that formulating a carbon tax rule for emissions targets results in a tool for policy advice that takes into account the political reality of policy makers. While parameters determining the social cost of carbon are uncertain, emission targets have been set by countries based on individual decision criteria and can as such be taken to inform "optimal" policy choice given the constraints of predefined ambition. Under the assumption that uncertainty in current IAMs is a key factor limiting policy uptake, this approach can deliver an insightful instrument for policy makers and a simplified modelling framework that is well suited to explain economic linkages to a wider audience.

To demonstrate this approach and the resulting changes in factors determining optimal carbon tax levels, a case study is introduced. Following the specifications of the DSGE model for optimal carbon taxes for fossil fuels of Golosov et al. 2012 [40], I demonstrate how introducing emission targets to a reduced general equilibrium setting can replace the damage function and result in a simplified but clear model for carbon taxes to reach pre-specified emission targets. With this approach, a given target emissions pathway can be directly translated into a corresponding tax pathway over time, requiring only input of common parameters for characterising the economy such as elasticity of substitution of production parameters and fuel intensity of sectors. This is not an improvement to the optimisation model but an alternative application, and results have to be interpreted in a distinct way. GHKT explicitly aim at deriving the optimal tax on fossil fuel. The model presented here does not identify the optimal tax level but identifies the tax required to reach any - optimal or not optimal - selected emissions level. The aim of introducing an emissions target is to build a model that can explain a different set of linkages and that is more applicable to the optimisation problem of a national policy maker as discussed in section 2. With reduced uncertainty, a level or range for the level of required tax can be determined that will be necessary to reach a selected target.

This model discusses solely optimal tax on emissions from the energy sector, but findings of this case study should be understood as exemplary for multi-sectoral models alike.

5. Method: A reduced DSGE model

5.1. *Golosov et al 2014*

With the aim of deriving a simple formula for the marginal externality damage of CO_2 emissions from the energy sector, Golosov, Hassler, Krusell and Tsyvinski (hereafter GHKT) develop their 2014 dynamic stochastic general-equilibrium model for an economy that utilises fossil energy for production [40]. From a global perspective, the size of the externality of fossil energy corresponds to the optimal tax level on fossil fuels in their simplified setting.

Based on four important assumptions, a tax formula is derived that defines the optimal tax level over time, independent of future technology, productivity or the future energy mix. Key assumptions are

1. utility is logarithmic in consumption
2. damages from emissions are proportional to output and can be defined as a function of total atmospheric carbon concentration
3. carbon levels can be expressed as a constant function of past and current emissions
4. consumers savings rate is constant.

The model is stochastic, in that it is possible to introduce a stochastic damage function and state dependent Arrow-Debreu prices. The former is applied to reflect the characteristics of potential damage from climate change, including fat tails and tipping points. The latter is a standard formal specification that representative agents can make state (and price) dependent decisions. These model characteristics define how GHKT treat uncertainty in their model.

Rationale for all assumptions is provided in GHKT 2014 and further discussed by Barrage 2014 [8] . In addition to these assumptions, the GHKT model requires the standard IAM parameter decisions on discounting, the scale of damage from climate impacts as well as the lifespan of CO2 in the atmosphere. For computational simplification, the authors furthermore introduce finite global oil reserves that will be used up within the next hundred years.

GHKT conclude that the time-path of oil extraction has only marginal importance for climate outcomes, while management of coal resources is key, due to the large availability of the latter. Second, they find that assumptions on technology, in particular on substitutability of energy forms, are key determinants of the cost of policy inaction, defined as the difference in total outputs over time between a taxed economy and a laissez-faire economy. Third, and most prominently, GHKT find that in their setting the optimal carbon tax, if implemented as a per-unit tax on units of emissions, can be expressed as a fraction of GDP over time.

Their general model is a multi-sector neoclassical growth model that includes a representative household consuming a final good, produced by a final-goods sector. Energy is the only intermediate good, produced by a number of intermediate-goods sectors, energy firms. Energy firms can be producing renewable energy or fossil fuel powered energy; energy units from these firms have distinct emission intensities and are not perfect substitutes. Output of the final-goods sector is a function of the inputs capital, labor and energy, but is also negatively affected by the amount of carbon in the atmosphere, which is assumed to be a sufficient proxy for temperature change in the economy. Carbon partly depreciates from the atmosphere each year and the current stock of carbon in the atmosphere is the only determinant for damage to output in year t. In equilibrium, the production factors capital, labor, and energy are allocated fully across sectors.

In the most general specification, assuming assumptions 1-3 hold, the marginal externality damage in GHKT's 2014 model, Λ_t^s, is

$$\Lambda_t^s = \mathbb{E}_t \sum_{j=0}^{\infty} \beta^j C_t \frac{Y_{t+j}}{C_{t+j}} \gamma_{t+j} \left(1 - d_j\right) \tag{2}$$

where $\beta \in (0,1)$ is the discount factor, C_t is consumption, Y_t is output, γ_t the time dependent damage parameter, and $1 - d_j$ the share of carbon that will not have depreciated after j periods. Assuming a constant savings rate s (Assumption 4) and taking into account that $C_t = sY_t$ this simplifies to

$$\Lambda_t^s = Y_t \left[\mathbb{E}_t \sum_{j=0}^{\infty} \beta^j \gamma_{t+j} \left(1 - d_j\right) \right] \tag{3}$$

Equation 3 is an interesting consequence of previous assumptions, as it states that the marginal externality cost of emissions as a share of GDP can be expressed as a function of the discount factor, the damage parameter (may be state and time contingent) and the carbon cycle. Equation 3 thereby suggests that future productivity or output does not affect marginal costs of emissions today. While future damages are defined as a share of output, the logarithmic utility function causes perfect offsets between higher (lower) damages from higher (lower) levels of output and lower (higher) marginal utility of output due to decreasing marginal utility of consumption. Following Pigou, the expression for the marginal externality cost of emissions also represents the optimal tax on carbon emissions, which incentivises the consumer to internalize the externality.[10]

The authors first compare their result for the optimal tax rate with findings of comparable models, for example Nordhaus and Boyer 2000 [44] or Stern 2007 [56], and find that they arrive at comparable estimates to Nordhaus and Boyer after making similar parameter choices than they did, while this is not the case for Stern 2007. The authors then use their optimal tax rate result to evaluate current policies in different jurisdictions, where they find that the EU ETS emission price in 2010-2012 corresponds relatively well with their result, assuming "standard" discount rates. Furthermore, it is possible to compute paths for key variables output, energy consumption by source and climate damage for a business-as-usual scenario and compare it to outcomes of an economy with optimal taxes on emissions. If the full model is laid out in this way, it is possible to translate the optimal carbon tax into optimal quantity restrictions over time, as would be applied in an emissions trading scheme.

In contrast to calculating the marginal damage from emissions, calculating the future path of the economy under both settings requires detail on characteristics of all endogenous variables in the model, for example extraction costs, substitutability of energy sources and technological change, and all exogenous parameters matter. In this context, the authors argue that it is an important advantage of their optimal-tax formula that it can be computed without these detailed assumptions, and that this advantage is furthermore an argument for using taxes over using quantity restrictions in climate policy. Table 2 gives an overview of all assumptions required to calculate the optimal tax rate in GHKT 2014 on the one hand, and the optimal level of emissions, again following GHKT, on the other hand.

[10] GHKT acknowledge that this does only hold in the absence of distortionary taxation and other market limitations. The topic of optimal carbon taxes with prior distortions has been analysed by Goulder 1995 [19], among others.

Table 2: Parameters required for calculating optimal policy choice for price and quantity mechanisms, based on the example of GHKT 2014

Policy type	Required parameters	Model outputs
Optimal carbon tax	Discount factor Damage parameter Carbon cycle	Optimal tax on fossil fuel emissions as a share of GDP for all t E (0, inf)
Optimal quantity regulation (ETS)	Discount factor Damage parameter Carbon cycle Initial stocks of fossil resources Productivity of all sectors Availability of labor Relative productivity of energy sources Degree of substitutability of energy forms (not exhaustive)	Optimal emission pathway over time and corresponding predicted output, temperature, energy use and resource depletion

Source: Author, based on GHKT 2014

5.2. *New assumptions and rationale for introducing an emission target*

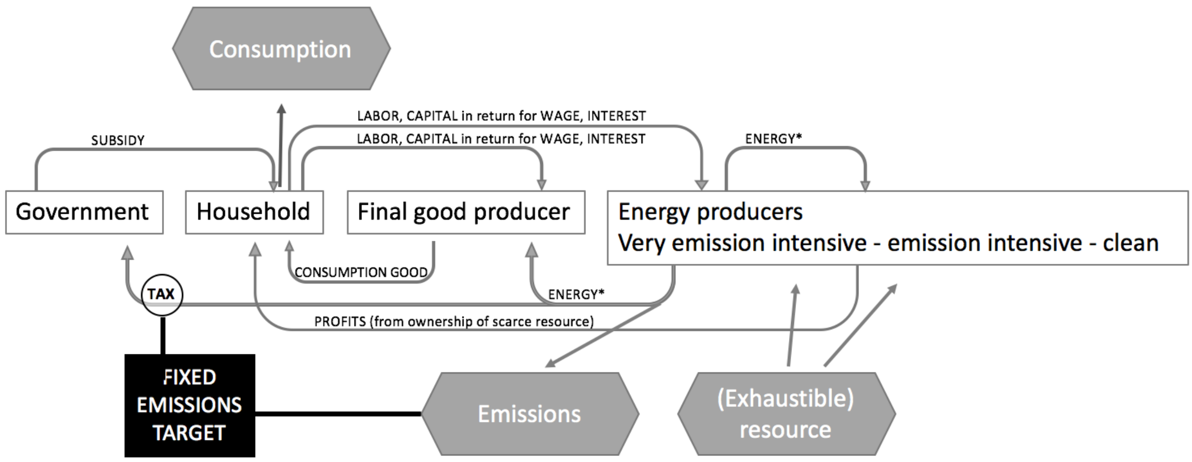
The multi-sector neo-classical growth model setting by GHKT can be used to demonstrate how the introduction of an emissions target in the place of the damage function changes parameter sensibility and moves the source of uncertainty from the damage function to characteristics of the economy. Taking a highly stylised approach, the following model abstracts from important economic characteristics of the economy. However, a high level of abstraction also facilitates understanding of model behaviour and increases the focus on key aspects analysed.

Figure 3 provides a schematic overview of the framework under GHKT less the carbon cycle and corresponding climate feedback to the economy. A fixed emissions target (highlighted in black) is added to this framework. The carbon tax rate is set so that the economy in equilibrium produces emissions as set in the target.

This modelling approach requires a number of changes to the GHKT setting. First, it is necessary to solve for the decentralised solution of the deterministic time infinite horizon problem of a economy in general equilibrium with taxes on fossil energy rather then solving the social planners problem, as the First and Second Welfare theorems no longer hold in the presence of a distorting tax. Second, an emissions target is introduced so that the tax can be calibrated against it.

Furthermore, a number of simplifications are introduced that do not reduce the explanatory power of the results in the context of this study: Energy producing sectors do not require capital or energy for production. Therefore, labor is the only shared factor between the output firm and all energy producers. Secondly, the economy is reduced to only include 2 energy sectors, of which one produces fossil energy, subject to a unit tax on the energy output, and one produces renewable energy, not subject to the tax. The fossil energy sector is not resource constrained. The argument for this adjustment is that, as demonstrated by GHKT and others, oil is not a key determinant of the long-run emission intensity of an

Figure 3: Schematic of the theoretical framework introduced by GHKT and introduction of an emissions target informing the tax rate (black)



Source: Author's depiction
(*)Simplified depiction. 3 distinct energy production sectors (emission intensive energy producers, emission intensive energy producers and clean energy producers) produce 3 energy types that are not perfect substitutes.

economy as it is being depleted in the short run. For the case of this argument it is therefore sufficient to introduce only one exemplary fossil energy sector with available resource that is sufficiently large to not be fully exhausted in the long run. For simplification, stochastic elements of the GHKT model are not included here.

5.3. *Characterisation*

The following section details an adjusted specification of the theoretical framework presented by GHKT. For details on the GHKT general model see GHKT 2014 [40].

The **representative consumer** has preferences for consumption C_t and maximises

$$\max_{\{C_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t ln\left(C_t\right)$$

subject to

$$\sum_{t=0}^{\infty} C_t + K_{t+1} = \sum_{t=0}^{\infty} \left(1 + r_t - \delta\right) K_t + w_t N_t + T_t + \Pi$$

where K_t denotes the aggregate capital stock in the economy, r_t is the interest due on capital, δ denotes annual depreciation and w_t the wage paid for labour N_t. In addition to capital and wage income, the representative household receives a lump-sum tax rebate of T_t and accumulated profits from all sectors Π. There are two boundary conditions on the resource constraint, $K_0 = k_0$ and the transversality condition.

The **final output firm** maximises

$$\Pi_0 \equiv \max_{\{K_t, N_{0,t}, E_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t F(K_t, N_{0,t}, E_t) - r_t K_t - w_{0,t} N_{0,t} - \sum_{i=1}^{2} p_{i,t} E_{i,t})$$
$$= \max_{\{K_t, N_{0,t}, E_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t (A_{0,t} K_t^{\alpha} N_{0,t}^{1-\alpha-\nu} E_t^{\nu} - r_t K_{0,t} - w_{0,t} N_{0,t} - \sum_{i=1}^{2} p_{i,t} E_{i,t})$$

subject to non-negativity constraints. $A_{i,t}$ is an exogenous, sector and time specific technology parameter, E_t denotes energy consumed by the final output firm. The two energy types have distinct prices $p_{i,t}$. The final output firm operates under perfect competition, output is priced at unity. E_t is an energy composite of fossil and clean energy:

$$E_t = \left(\kappa_1 E_{1,t}^{\rho} + \kappa_2 E_{2,t}^{\rho}\right)^{1/\rho}$$

and $\sum_{i=1}^{2} \kappa_i = 1$. $\rho < 1$ is the parameter for elasticity of substitution between energy sources, κ_i measures relative efficiency.

A **representative fossil energy firm** maximises

$$\Pi_1 \equiv \max_{\{N_{1,t}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t ((p_{1,t} - \tau_t) E_{1,t} - w_{1,t} N_{1,t})$$

The fossil energy firm is not resource constrained and produces with labour as its only input.

$$E_{1,t} = A_{1,t} N_{1,t}$$

A **representative renewable energy firm** maximises

$$\Pi_2 \equiv \max_{\{N_{2,t}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t (p_{2,t} E_{i,t} - w_{2,t} N_{2,t})$$

The renewable energy firm is not resource constrained and produces with labour as its only input.

$$E_{2,t} = A_{2,t} N_{2,t}$$

$E_{1,t}$, fossil energy, is expressed in units of carbon content, the introduced tax τ_t is a per unit tax on carbon units. $E_{2,t}$, renewable energy has a carbon content of 0 and is normalised so that it's relative productivity to the fossil energy unit is unity ($\kappa_1 = \kappa_2$). Labour is constrained and normalised. There is no total labour growth, but labour growth could be introduced.

$$N_{0,t} + N_{1,t} + N_{2,t} = N = 1$$

Aggregate profits are defined as

$$\Pi = \sum_{i=0}^{2} \Pi_i$$

but in perfect competition only ownership of the scarce resource brings profits. There is a government transfer of

$$T_t = \tau_{1,t} E_{1,t}$$

There is a set target for emissions $E_{1,t}$ by time period, denoted by

$$Z_t = z_t$$

5.4. *Solving the model*

5.4.1 *Markets clear*

Each production input is valued at its marginal productivity.

$$w_{0,t} = F'_{N_{0,t}}(K_t, N_{0,t}, E_t)$$

$$r_t = F'_{K_t}(K_t, N_{0,t}, E_t)$$

$$p_{1,t} = F'_{E_{1,t}}(K_t, N_{0,t}, E_t)$$

$$p_{2,t} = F'_{E_{2,t}}(K_t, N_{0,t}, E_t)$$

It follows that wage $w_{0,t}$ can be expressed as

$$w_{0,t} = \frac{(1 - \alpha - \nu)F(K_t, N_{0,t}, E_t)}{N_{0,t}} \tag{4}$$

interest r_t paid on capital as

$$r_t = \frac{\alpha F(K_t, N_{0,t}, E_t)}{K_t} \tag{5}$$

and the respective energy inputs are priced at their marginal productivity,

$$p_{1,t} = \frac{\kappa_1 \nu E_{1,t}^{\rho-1} F(K_t, N_{0,t}, E_t)}{E_t} \tag{6}$$

$$p_{2,t} = \frac{\kappa_2 \nu E_{2,t}^{\rho-1} F(K_t, N_{0,t}, E_t)}{E_t} \tag{7}$$

Total energy produced is equal to total energy consumed in any period.

$$E_{1,t} = A_{1,t} N_{1,t} \tag{8}$$

$$E_{2,t} = A_{2,t} N_{2,t} \tag{9}$$

Furthermore, in equilibrium, marginal productivity of labour is equal across all 3 sectors under optimal labour allocation.

$$w_{0,t} = w_{2,t} = w_{3,t} \tag{10}$$

5.4.2 *First-order conditions of representative agents*

The Lagrangian for the optimisation problem of the consumer becomes

$$\mathcal{L} = \sum_{t=0}^{\infty} \beta^t [ln(C_t) + \lambda_t[(1 + r_t - \delta)K_t + w_t N_t + T_t + \Pi - C_t - K_{t+1}]]$$

. Combining the first-order conditions with respect to C_t and K_{t+1} generates the Euler equation.

$$\frac{1}{C_t} = \frac{1}{C_{t+1}} \beta\alpha \frac{F(K_{t+1}, N_{0,t+1}, E_{t+1})}{K_{t+1}}$$

Assuming a constant savings rate following GHKT, the Euler equation is solved by

$$K_{t+1} = \alpha\beta F(K_t, N_{0,t}, E_t) \tag{11}$$

Replacing E_t with the definition of the energy composite and setting $\kappa_1 = \kappa_2 = 0.5 = \kappa$, the optimisation problem of the final good producer becomes

$$\max_{\{K_t, N_{0,t}, E_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t [A_{0,t} K_t^{\alpha} N_{0,t}^{1-\alpha-\nu} ((\kappa E_{1,t}^{\rho} + \kappa E_{2,t}^{\rho})^{1/\rho})^{\nu} - r_t K_{0,t} - w_{0,t} N_{0,t} - p_{1,t} E_{1,t} - p_{2,t} E_{2,t}]$$

Deriving the FOCs with respect to $E_{1,t}$, $E_{1,t}$:

$$p_{1,t} = \nu A_{0,t} K_t^{\alpha} N_{0,t}^{1-\alpha-\nu} \kappa E_{1,t}^{\rho-1} (\kappa E_{1,t}^{\rho} + \kappa E_{2,t}^{\rho})^{\frac{\nu}{\rho}-1} \tag{12}$$

$$p_{2,t} = \nu A_{0,t} K_t^{\alpha} N_{0,t}^{1-\alpha-\nu} \kappa E_{2,t}^{\rho-1} (\kappa E_{1,t}^{\rho} + \kappa E_{2,t}^{\rho})^{\frac{\nu}{\rho}-1} \tag{13}$$

Similarly, the FOCs of the energy sectors with respect to $N_{1,t}$ and $N_{2,t}$, respectively:

$$w_{1,t} = (p_{1,t} - \tau_t) A_{1,t} \tag{14}$$

$$w_{2,t} = p_{2,t} A_{2,t} \tag{15}$$

Equilibrium in this economy is described by the optimal allocation of labour between the three sectors and corresponding production levels of energy and output.

5.4.3 *Solution*

The aim is to express emissions in year t, $E_{1,t}$, as a function of the carbon tax in order to then be able to express the carbon tax as a function of a set emissions target, $E_{1,t} = Z_t$, and all necessary characteristics of the economy.

$$E_{1,t} = G(\tau_t, A_{1,t}, A_{2,t}, A_{0,t}, K_t, \rho, \nu, \alpha) \tag{16}$$

$$\tau_t * = G(Z_t, A_{1,t}, A_{2,t}, A_{0,t}, K_t, \rho, \nu, \alpha) \tag{17}$$

From equations 12, 13 it follows that

$$E_{2,t} = E_{1,t} \left(\frac{p_{2,t}}{p_{1,t}} \right)^{\frac{1}{\rho-1}} \tag{18}$$

Filling in for $E_{2,t}$, $p_{1,t}$ and $p_{2,t}$ from equations 18, 14 and 15 in equation 12 then results in

$$E_{1,t}^{\rho-1} \left(\kappa E_{1,t}^{\rho} + \kappa (E_{1,t} (\frac{A_{1,t} w_t}{A_{2,t} w_t + A_{1,t} A_{2,t} \tau})^{\frac{1}{\rho-1}})^{\rho} \right)^{\frac{\nu}{\rho}-1} = \frac{\frac{w_t}{A_{1,t}} + \tau}{\nu A_{0,t} K_t^{\alpha} N_{0,t}^{1-\alpha-\nu} \kappa} \tag{19}$$

where w_t is the equilibrium wage across all sectors:

$$w_t = \frac{(1-\alpha-\nu)A_{0,t}K_t^{\alpha}N_{0,t}^{1-\alpha-\nu}((\kappa E_{1,t}^{\rho}+\kappa E_{2,t}^{\rho})^{1/\rho})^{\nu}}{N_{0,t}}$$

$$E_{1,t} = A_{1,t}N_{1,t} \tag{20}$$

$$E_{2,t} = A_{2,t}N_{2,t} \tag{21}$$

$$N_{0,t} + N_{1,t} + N_{2,t} = N = 1 \tag{22}$$

Together with equations 20-22, we have established an equation system in 5 equations and 5 unknowns ($E_{1,t}$,$E_{2,t}$,$N_{0,t}$,$N_{1,t}$,$N_{2,t}$) that can be solved computationally. K_t follows an earlier defined path (equation 11) based on the assumption of a constant savings rate.

Intuitively, the carbon tax τ_t appears as an increasing factor for the market price of the fossil energy input, and also as a decreasing factor for the relative size of fossil energy in the economy.

5.5. *Calibration*

This model can be calibrated as follows. α, ν, and δ are standard parameters in economic modelling and can be calibrated based on usual considerations. In this taxed economy setting β, the discount rate, is only required for finding the savings rate of the consumer. The savings rate could itself be treated as a parameter, in order to avoid calibrating for a discount rate. For the elasticity of substitution between fossil and renewable energy, ρ, various metastudies are available. Given a long-run elasticity σ, ρ can be obtained as $\sigma = 1/(1+\rho)$. K_0 is calibrated to a selected net rate of return (capital returns less depreciation) and furthermore depends on annual GDP, so that $K_0 = \frac{\alpha(GDP)}{r+\delta}$.

Finally, the normalisation of energy units needs to be considered when calibrating for productivity parameters. Starting with average extraction cost of one MWh-equivalent of coal or a representative fossil energy composite, $A_{1,0}$ can be derived since $p_1 = \frac{w}{A_1}$ in the absence of a tax. Similarly, $A_{2,0}$ is then derived based on the average cost of generating one MWh renewable energy. Productivity growth in all sectors is exogenously defined and can be calibrated in line with standard choices for productivity growth, or aligned to a model of comparison.

6. Results

6.1. *Main Results*

From equation 19 it is possible to conclude that given the model specifications, the formula for a carbon tax given an emission target has the following form.[11]

$$\tau_t * = G(Z_t, A_{1,t}, A_{2,t}, A_{0,t}, K_t, \rho, \nu, \alpha) \tag{23}$$

In addition to the parameters listed above, the theoretical calibration exercise in Section 5.5 showed indirectly required parameters such as cost of energy generation. Table 3 presents a comparison of required parameters for calculating an optimal carbon tax following GHKT, as well as the set of required parameters under a target-to-tax scheme as demonstrated here.

Table 3: Parameters required for calculating optimal policy choice for price and quantity mechanisms, based on the example of GHKT 2014

Policy type	Required parameters	Model outputs
Optimal carbon tax	Discount factor Damage parameter Carbon cycle	Optimal tax on fossil fuel emissions as a share of GDP for all t E (0, inf)
Carbon tax given a (dynamic) emission target	Emission target (annual) Relative productivity of production factors Discount factor or savings rate Degree of substitutability of energy forms Productivity of all sectors Productivity growth of all sectors Relative prices of energy sources (generation costs)* GDP* Net rate of capital return* (list extends with increasing modeling detail. for example: Availability of labor, Initial stocks of fossil resources (if applicable))	Required (unit) tax on fossil fuel emissions necessary to reach a specified target under given assumptions

Source: Author

(*) Parameter does not appear in equation but is required for calibration.

It is clear that the number or required parameters expands for a target-to-tax scheme as compared to the optimal tax of GHKT. In fact, under identical model characterisation, the formula for a carbon tax given an emission target is a function of all parameters that are also required for optimal quantity choice, except for the damage parameter, the carbon cycle, and the depreciation rate appears in a less decisive role. GHKT argue that the possibility to estimate the optimal carbon tax based on only the discount factor, the damage parameter and the carbon cycle is a clear advantage of the carbon tax as an instrument over quantity based cap and trade instruments [40]. Contrasting the longlist of parameters required for a target-to-tax scheme to the three required input parameters for optimal carbon tax, it is

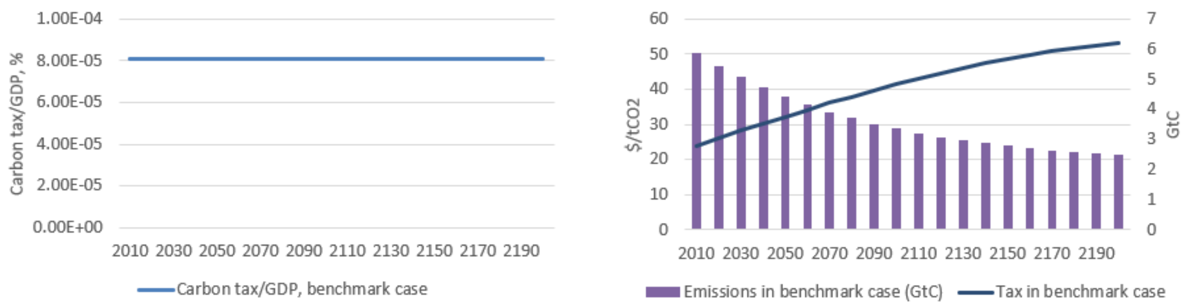
[11] Note that κ still appears in equation 19 for formal reasons. It has however been set to 0.5, as renewable energy units are normalised accordingly.

clear that the former -with exception of the emissions target- all belong to a parameter set that is more standard in economic modelling and that is easier to access and test.

The two modelling approaches require distinctively different inputs and solve separate problems, and should therefore not be understood as competing models. It was demonstrated that reduced uncertainty in the modelling framework can be gained at the cost of giving up Pareto optimality of outcomes. This result is only valuable in the context of emissions targets that are discussed independently of optimal policy choice and that are not strictly informed by climate-economy models. Emission targets as set in NDCs could provide this context.

In a perfect information setting, the optimal emission pathway would be available and the reduced target-to-tax approach would be identical to the full IAM optimisation for the optimal carbon tax. Without perfect information, the full IAM optimisation is subject to severe uncertainty, while the carbon-to-tax mechanism is, in addition to relatively less severe uncertainty, blind to the risk of applying an inefficient target and the related costs of wrong policy choice. However, this risk may be negligible where climate politics do not discuss long run economic efficiency and long run optimisation as much as current constraints and political interests. In this sense, a target-to-tax mechanism may achieve better results, as it increases accountability and - once the target has been set - all required considerations can be limited to a near term time horizon. Figure 4 illustrates the key results of the two modelling approaches. On the left hand side, the optimal tax over time as a share of GDP is presented as resulting from the GHKT model under baseline assumptions. On the right hand side of Figure 4, the result of a target-to-tax approach, expressed as an annual level of a unit tax on carbon emissions, is depicted under equal assumptions, based on the optimal emissions pathway derived in GHKT.

Figure 4: Comparison of key outputs of reference model (left) and target-to-tax approach (right) under a baseline scenario



Source: Author's depiction, left Figure based on GHKT 2012/Barrage 2012 [40, 8]
(*)This depiction assumes a baseline case of logarithmic utility, constant factor productivity and full depreciation over the 10 year time period. Emission targets in the target-to-tax case are assumed to be set optimal (in line with results of reference model).

What is presented here is only an exemplary case for re-framing an existing climate-economy model. Similar applications are possible for the whole class of sector specific DSGE and ABMs modelling sufficient detail of the economy. While this paper is likely not the first one to frame the carbon tax policy setting problem in this way, it is the first one to discuss and contrast this approach to policy optimisation under standard integrated assessment models.

6.2. *Limitations*

Eliminating the damage parameter from the policy optimisation model comes at the cost of model reliance to other assumptions, most importantly technological change, and elasticity of substitution between different sources of energy. Barrage conducted a detailed sensitivity analysis of GHKT 2014 to a set of parameters including total factor productivity, depreciation rate and the discount factor, and highlights large sensitivities around all three. Similarly, an extended sensitivity analysis on parameters in the target-to-tax framework would be necessary to be able to fully assess what drives results in this framework and how drivers change across the two settings.

A key limitation of the target-to-tax approach is that it is blind to potential for policy improvement. By definition, the resulting tax rate is not necessarily the optimal tax rate, and the model does not tell us what the cost are of not achieving the optimum.

The carbon-to-tax approach may or may not be closely linked to science. It is not ruled out that the emissions target is derived from climate economy models, but it is also not prescribed. There is a clear model reliance on an emissions target as input. In this sense, the model does not try to stand on its own but fits into the existing model landscape, being assessed next to "sister" models it draws from. It is worth noting that not all emissions targets that are formulated are formulated based on cost benefit optimisation thoughts. Targets may also result from the design of an "avoid" scenario, where a target is set to prevent unwanted outcomes. In the face of policy choice that is not solely centered around economic efficiency, conventional policy optimisation is constrained and a richer set of target-to-tax approaches would be of use.

The argumentation in this study is relying on the assumptions that uncertainty is a limiting factor to policy uptake. While there is evidence that this is the case, there remains room for research on barriers to climate policy uptake and their respective importance. A survey based case study of environmental policy choice under scientific uncertainty by Di Lucia et al. 2012 conducted in the European Union identified three common approaches to policy choice under uncertainty: Neglecting uncertain knowledge, treating uncertain knowledge as certain, and precaution [33]. It remains to be verified if this is the case in the context of climate policy, and if so, what factors determine which approach is taken by policymakers. The target-to-tax model can serve well as tool for policy makers choosing either of the two latter approaches to policy choice under uncertainty. The first approach (neglecting uncertain knowledge) corresponds to the observation of low climate mitigation policy uptake globally.

This study did not cover any carbon tax design elements other than tax level. Neither are policy linkages discussed. Nevertheless, carbon tax design elements around carbon leakage prevention, equity effects, policy interaction, or trade effects, to name a few, are key for policy success and their importance for a coherent an effective climate policy landscape is acknowledged.

6.3. *Policy implications*

6.3.1 *Carbon tax with emissions target versus carbon market*

Carbon tax with emission targets and carbon markets (emissions tradings systems) may appear related from a design perspective, but are very distinctive concepts. While both mechanisms are designed with respect to a target, a target-to-tax policy as discussed here will not necessarily result in emission levels that match the suggested carbon targets, unless a TAMPP is proposed[21]. In the absence of a tax adjustment mechanism, the standard instrument characteristics apply and the target-to-tax approach results in price certainty only, while an ETS results in quantity certainty [29]. The benefit of a target-to-tax approach over a common carbon tax approach is not certainty over emissions quantities, but rather that it can support transparency of ambition and accountability in the moment of policy choice. When comparing the target-to-tax approach to an ETS, most arguments of the debate over pricing instrument choice apply unchanged, with the exception of arguments around required parameter inputs.

6.3.2 *Current gaps in research*

To my knowledge, there has not been prominent research conducted on the topic of discussing emissions targets alongside carbon tax optimisation. While this approach is not novel, it has benefits for model transparency, model clarity and policy explanation that have not received substantial attention.

This study discussed the trade-off between global optimisation and second best options as achieved through a target-to-tax approach. There are interesting avenues for research around quantifying these trad-offs in a multidimensional way, including sensitivities to parameter selection, implementation constraints, and risks and costs of inefficient policy choice.

Furthermore, as discussed earlier, there appears to be a lack of analysis combining results of economic models with the perspective of policy makers. Such analysis would approach the problem of optimal policy choice centered around policy makers incentives and constraints. Related to this, future research could potentially expand on existing hypotheses regarding current barriers to climate change policy uptake.

7. Conclusion

This study aimed to analyse the existing suite of economic models for climate policy optimisation from a policy makers perspective, with a focus on uncertainty of input parameters. This is important as global levels of carbon pricing remain low, despite economists agreeing on the urgent need for policy measures. Uncertainty is assumed to be a contributing factor to low policy uptake globally. An alternative application of existing CGE modelling work was then suggested that addresses identified short-comings around major uncertainties by linking modelling efforts with existing national emission targets as submitted by countries under the UNFCCC.

It was demonstrated how model dependency on uncertain parameters in policy optimisation such as future damage from climate change and climate sensitivity can be shifted by introducing exogenously set emissions targets to the modelling framework. This is valuable as it results in a simple and intuitive framework that can serve as basis for discussion, depends on parameters that are more frequently discussed in other policy optimisation contexts, and that has a clear focus on emissions, as emissions levels have become central to the successful coordination of international policy efforts. Under the assumption that high uncertainty around parameters characterising the damage function and high model complexity limit the relevance of a model to policy makers, this target-to-tax approach can be a second-best option.

Importantly, quantity focused target-to-tax approaches are not improving efficiency of results as compared to IAMs. Instead, they add insights to the debate that can potentially facilitate policy uptake in a setting where first-best policy choice is not feasible. The two modelling approaches require different inputs and solve distinct problems, and should therefore not be understood as competing models.

This study argues that there should be a richer set of models that explicitly aim to inform climate policy makers in their decisions, taking into account their need for clarity, reduced uncertainty and a focus on annual emissions as central outcome.

References

[1] Frank Ackerman et al. "Limitations of integrated assessment models of climate change". In: *Climatic change* 95.3-4 (2009), pp. 297–315.

[2] International Energy Agency. "Real-world policy packages for sustainable energy transitions. Shaping energy transition policies to fit national objectives and constraints". In: *IEA Insight Series 2017* (2017).

[3] Doyne J. Farmer et al. "A Third Wave in the Economics of Climate Change". In: *Environmental and Resource Economics* 62.2 (2015), pp. 329–357.

[4] Richard Moss et al. "The next generation of scenarios for climate change research and assessment". In: *Nature: Perspectives* 463.11 (2010), pp. 747–757.

[5] Myles R Allen and David J Frame. "Call off the quest". In: *Science* 318.5850 (2007), pp. 582–583.

[6] Kenneth J Arrow et al. *Intertemporal equity, discounting, and economic efficiency.* Cambridge, UK, New York and Melbourne: Cambridge University Press, 1996.

[7] World Bank and Ecofys. *State and Trends of Carbon Pricing 2018.* IBRD/ The World Bank, 2018.

[8] Lint Barrage. "Sensitivity analysis for Golosov, Hassler, Krusell, and Tsyvinski (2013): Optimal taxes on fossil fuel in general equilibrium." In: *Technical Notes* (2013).

[9] Inge van den Bijgaart, Reyer Gerlagh, and Matti Liski. "A simple formula for the social cost of carbon". In: *Journal of Environmental Economics and Management* 77 (2016), pp. 75–94.

[10] Yongyang Cai, Kenneth L Judd, and Thomas S Lontzek. *The social cost of stochastic and irreversible climate change.* Tech. rep. National Bureau of Economic Research, 2013.

[11] Raphael Calel and David A. Stainforth. "On the physics of three integrated assessment models". In: *American Meteorological Society* (2017), pp. 1199–1216.

[12] Benjamin Crost and Christian P Traeger. "Optimal CO 2 mitigation under damage risk valuation". In: *Nature Climate Change* 4.7 (2014), p. 631.

[13] UK DECC. *Carbon Valuation in UK Policy Appraisal: A Revised Approach.* 2009.

[14] Hadi Dowlatabadi. "Integrated assessment models of climate change: An incomplete overview." In: *Energy Policy* 23.4-5 (1995), pp. 289–296.

[15] Trésor Economics. "Economic analysis of the Paris Agreement". In: *Ministère de l'Économie et des Finances* (2016), No. 187.

[16] P Enkvist, Tomas Nauclér, and Jerker Rosander. "A cost curve for greenhouse gas reduction". In: *McKinsey Quarterly* 1 (2007), p. 34.

[17] EPA. "Technical Support Document: Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866". In: (2010).

[18] Wilman Gomez et al. *A DSGE Model with loss aversion in consumption and leisure: An explanation for business cycles aymmetries*. Tech. rep. 2014.

[19] Lawrence H Goulder. "Effects of carbon taxes in an economy with prior tax distortions: an intertemporal general equilibrium analysis". In: *Journal of Environmental economics and Management* 29.3 (1995), pp. 271–297.

[20] Lawrence H. Goulder and Ian W.H. Parry. "Instrument Choice in Environmental Policy". In: *RFF Discussion Paper* 07 (2008).

[21] Marc Hafstead, Gilbert E Metcalf, and Roberton C Williams III. "Adding quantity certainty to a carbon tax through a tax adjustment mechanism for policy precommitment". In: *Harv. Envtl. L. Rev. F.* 41 (2017), p. 41.

[22] Christina Hood and Carly Soo. "Accounting for mitigation targets in Nationally Determined Contributions under the Paris Agreement". In: *CCXG/OECD* (2017).

[23] Chris Hope, John Anderson, and Paul Wenman. "Policy analysis of the greenhouse effect: an application of the PAGE model". In: *Energy Policy* 21.3 (1993), pp. 327–338.

[24] IPCC. *Climate Change 2001: Synthesis Report. Contribution of Working Groups I, II and III to the Third Assessment Report of the Intergovernmental Panel on Climate Change*. IPCC, Cambridge University Press, 2001.

[25] IPCC. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. IPCC, Geneva, Switzerland, 2014.

[26] IPCC. *Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*. World Meteorological Organization, Geneva, Switzerland, 2014.

[27] IPCC. *National and Sub-national Policies and Institutions. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. IPCC, Cambridge University Press, 2014.

[28] Jesse D Jenkins. "Political economy constraints on carbon pricing policies: What are the implications for economic efficiency, environmental efficacy, and climate policy design?." In: *Energy Policy* 69 (2014), pp. 467–477.

[29] Paul Lehmann and Erik Gawel. "Carbon taxes versus cap and trade: a critical review." In: *Climate Change Economics* 4.3 (2013), p. 1350010.

[30] Paul Lehmann and Erik Gawel. "Why should support schemes for renewable electricity complement the EU emissions trading scheme?." In: *Energy Policy* 52 (2013), pp. 597–607.

[31] Derek Lemoine and Christian Traeger. "Watch your step: optimal policy in a tipping climate". In: *American Economic Journal: Economic Policy* 6.1 (2014), pp. 137–66.

[32] Richard G Lipsey and Kelvin Lancaster. "The general theory of second best". In: *The review of economic studies* 24.1 (1956), pp. 11–32.

[33] Karin Ericsson Lorenzo Di Lucia Serina Ahlgren. "The dilemma of indirect land-use changes in EU biofuel policy – An empirical study of policy-making in the context of scientific uncertainty". In: *Environmental Science and Policy* 16 (2012), pp. 9–19.

[34] Alan Manne, Robert Mendelsohn, and Richard Richels. "MERGE: A model for evaluating regional and global effects of GHG reduction policies". In: *Energy policy* 23.1 (1995), pp. 17–34.

[35] Alex L. Marten. "Transient Temperature Response Modeling in IAMs: The Effects of Over Simplification on the SCC." In: *Economics: The Open-Access, Open-Assessment E-Journal* 5 (2011), pp. 1–42.

[36] Rajnish Mehra and Edward C. Prescott. "The equity premium in retrospect." In: *Handbook of the Economics of Finance* 1 (2003), pp. 889–938.

[37] Gilbert E Metcalf et al. "Reacting to Greenhouse Gas Emissions: A Carbon Tax to Meet Emission Targets". In: *Unpublished manuscript, Tufts University Department of Economics* (2009).

[38] Gilbert E Metcalf, James Stock, et al. *The role of integrated assessment models in climate policy: A user's guide and assessment*. Department of Economics, Tufts Univ., 2015.

[39] Clément Métivier et al. *Global panorama of carbon prices in 2017*. 2017.

[40] Per Krusell Mikhail Golosov John Hassler and Aleh Tsyvinski. "Optimal taxes on fossil fuel in general equilibrium". In: *Econometrica* 82.1 (2014), pp. 41–88.

[41] William D. Nordhaus. "A review of the Stern review on the economics of climate change." In: *Journal of economic literature* 45.3 (2007), pp. 686–702.

[42] William D. Nordhaus. *Efficient use of energy resources*. 1979.

[43] William D. Nordhaus. "The'dice'model: Background and structure of a dynamic integrated climate-economy model of the economics of global warming." In: *Cowles Foundation for Research in Economics* 1009 (1992).

[44] William D Nordhaus and Joseph Boyer. *Warming the world: economic models of global warming*. MIT press, 2000.

[45] William D. Nordhaus and Zili Yang. "A regional dynamic general-equilibrium model of alternative climate-change strategies." In: *The American Economic Review* 86.4 (1996), pp. 741–765.

[46] Robert S. Pindyck. “Climate change policy: what do the models tell us?” In: *Journal of Economic Literature* 51.3 (2013), pp. 860–872.

[47] Robert S. Pindyck. “Modeling the Impact of Warming in Climate Change Economics”. In: *The Economics of Climate Change: Adaptations Past and Present, edited by Gary D. Libecap and Richard H.Steckel* (2011), pp. 47–72.

[48] Robert S Pindyck. “The use and misuse of models for climate policy”. In: *Review of Environmental Economics and Policy* 11.1 (2017), pp. 100–114.

[49] Robert S. Pindyck. “Uncertainty in Environmental Economics”. In: *NBER Working Paper Series* 12752 (2006).

[50] William Pizer et al. “Using and improving the social cost of carbon”. In: *Science* 346.6214 (2014), pp. 1189–1190.

[51] David Stainforth Simon Dietz Raphael Calel. “Tall tales and fat tails: the science and economics of extreme warming.” In: *Climatic Change* 132.1 (2015), pp. 127–141.

[52] Armon Rezai and Frederick Van der Ploeg. “Intergenerational inequality aversion, growth, and the role of damages: Occam’s rule for the global carbon tax”. In: *Journal of the Association of Environmental and Resource Economists* 3.2 (2016), pp. 493–522.

[53] Cameron Hepburn Samuel Fankhauser and Jisung Park. “Combining multiple climate policy instruments: how not to do it.” In: *Climate Change Economics* 1.3 (2010), pp. 209–225.

[54] Peter Schwartz. *The Art of the Long View: Planning for the Future in an Uncertain World*. Doubleday, 1996.

[55] Nicholas Stern. “Economics: current climate models are grossly misleading.” In: *Nature NEws* 530.7591 (2016), p. 407.

[56] Nicholas Stern. *Stern Review: The economics of climate change.* HM treasury, 2006.

[57] J.E. et al. Stiglitz. *Report of the High-Level Commission on Carbon Prices*. IBRD and IDA / The World Bank, 2017.

[58] Richard SJ Tol. “On the optimal control of carbon dioxide emissions: an application of FUND”. In: *Environmental Modeling Assessment* 2.3 (1997), pp. 151–163.

[59] Detlef P van Vuuren et al. “How well do integrated assessment models simulate climate change?” In: *Climatic change* 104.2 (2011), pp. 255–285.

[60] Martin L. Weitzman. “A review of the Stern Review on the economics of climate change.” In: *Journal of economic literature* 45.3 (2007), pp. 703–724.

[61] John Weyant. “Some contributions of integrated assessment models of global climate change.” In: *Review of Environmental Economics and Policy* 11 (2017), pp. 115–137.

[62] Jeanne Anderer Wolf Häfele and Alan Macdonald. *Energy in a finite world: Paths to a sustainable future*. Ballinger Publishing Company, 1981.

Appendix A - NDCs and carbon tax levels by party to the Paris Agreement

The Paris Agreement required all nations that joined to declare NDCs. A NDC is a pledge to commit to emission reduction targets and other actions, and NDCs are to be renewed every five years. Contributions are voluntary in the sense that there is currently not a mechanism in place that ensures compliance, but the recently adopted Paris Rulebook (COP24) includes an improved common framework for reporting and reviewing progress. The first round of NDCs includes targets at least up to 2025, and the second round of NDCs, due by 2020, will require parties to state targets for the period up to 2030 at a minimum. Developed countries (Annex I parties) were asked to pledge economy-wide, absolute (including a basket of greenhouse gases) emissions targets, while developing countries (Non-Annex I) countries were given freedom to select targets appropriate to national circumstances. Table 4 provides a summary of most commonly applied mitigation targets in the firs round of NDCs. Table 5 provides a full list of NDC pledges and also lists the according explicit carbon pricing initiatives as reported in the World Bank Carbon Pricing Dashboard as of February 2019.

A large number of parties to the PA has decided to set mitigation targets relative to an emissions baseline ("baseline targets") in their NDC. Baseline targets define the mitigation contribution target of a party relative to a counterfactual business-as-usual baseline scenario (BAU). This practice requires clear and transparent baseline scenarios to avoid double-counting [22].

Table 4: Classification of NDCs by type of mitigation target (First NDC submission)

Type of mitigation target in NDC	Country NDCs with this target	Share of global GHG emissions
Absolute emission reduction	83	44,1%
Relative emission reduction	56	14,2%
Carbon intensity reduction	9	35,5%
Peak of carbon emissions	3	1,2%
Policies and actions	30	3,0%

Source: IGES NDC database, Version 6.3, April 2019; IEA 2018

Table 5: Overview of NDCs and carbon pricing initiatives by country

	Summary 1st NDC						Policy summary	
Country	Mitigation Type	Mitigation Target	Baseline Year	Target Year	NDC Coverage	% of global GHG 2015	ETS (Region, US$/tCO2)	Carbon tax (Region, US$/tCO2)
Afghanistan	Relative emission reduction	13,6%	BAU	2030	Economy-wide	N/A		
Afghanistan	Relative emission reduction	13,6%	BAU	2030	Economy-wide	N/A		
Albania	Relative emission reduction	11,5%	BAU	2030	Sectoral	0,02%		
Algeria	Relative emission reduction	7-22%	BAU	2030	Economy-wide	0,49%		
Andorra	Relative emission reduction	37%	BAU	2030	Economy-wide	N/A		
Angola	Relative emission reduction	50%	BAU	2030	Economy-wide	0,29%		
Antigua and Barbuda	Policies and actions	N/A	2006	2020 and 2030	Economy-wide	N/A		
Argentina	Relative emission reduction	18% unconditional, 37% conditional	BAU	2030	Economy-wide	0,78%		Argentina, 10
Armenia	Peak of carbon emissions	<663MtC02e and 189 tonnes per capita	N/A	2030	Economy-wide	0,02%		
Australia	Absolute emission reduction	26 to 28%	2005	2030	Economy-wide	1,27%	Australia, n/a	
Azerbaijan	Absolute emission reduction	35%	1990	2030	Economy-wide	0,11%		
Bahamas	Relative emission reduction	30%	BAU	2030	Economy-wide	N/A		
Bahrain	Policies and actions	N/A	N/A	2030	Sectoral	0,08%		
Bangladesh	Relative emission reduction	20% (5% unconditional, 15% conditional)	BAU	2030	Economy-wide	0,45%		
Barbados	Relative emission reduction	21% and 23%	2008	2025 and 2030	Economy-wide	N/A		
Belarus	Absolute emission reduction	28%	1990	2030	Economy-wide	0,22%		
Belize	Policies and actions	85% renewable energy increase	BAU	2030	Economy-wide	N/A		
Benin	Absolute emission reduction	16.7% (3.62% unconditional, 12.55% conditional)	2012	2030	Economy-wide	0,03%		
Bhutan	Absolute emission reduction	Remain carbon neutral	N/A	N/A	Economy-wide	N/A		
Bolivia	Policies and actions	N/A	N/A	2030	Economy-wide	0,12%		
Bosnia and Herzegovina	Absolute emission reduction	2% below BAU unconditional, 23% conditional	1990	2030	Economy-wide	0,06%		
Botswana	Absolute emission reduction	15%	2010	2030	Economy-wide	0,03%		
Brazil	Absolute emission reduction	37% by 2025, 43% by 2030 (indicative)	2005	2025	Economy-wide	2,51%	under consideration	under consideration
Brunei Darussalam	Policies and actions	63% of energy consumption reduction	BAU	2035	Sectoral	0,02%		
Burkina Faso	Absolute emission reduction	6.6% unconditional, 11.6% conditional	2007	2030	Economy-wide	N/A		
Burundi	Absolute emission reduction	3% unconditional, 20% conditional	2005	2030	Economy-wide	N/A		
Cambodia	Absolute emission reduction	27%	Baseline emissions of 11,600 Gg CO2eq	2030	Economy-wide	0,07%		
Cameroon	Absolute emission reduction	32%	2010	2035	Economy-wide	0,09%		
Canada	Absolute emission reduction	30%	2005	2030	Economy-wide	1,69%	various regional ETS, 15.7-22.9	Alberta, 22.9; British Columbia, 26.7

Cape Verde	Policies and actions	30% renewable energy target, 100% with international support	N/A	2025	Economy-wide	N/A		
Central African Republic	Absolute emission reduction	5% by 2030 and 25% by 2050	2010	2030	Economy-wide	N/A		
Chad	Absolute emission reduction	18.2% unconditional, 71% conditional	2010	2030	Economy-wide	N/A		
Chile	Carbon intensity reduction	30% unconditional emission intensity reduction, 35-45% conditional	2007	2030	Economy-wide	0,24%	Chile, n/a	Chile, 5
China	Carbon intensity reduction	60-65% carbon intensity reduction	2005	2030	Economy-wide	26,50%	various regional pilots, 1.1 -4.4	
Colombia	Relative emission reduction	20% unconditional, 30% conditional	BAU	2030	Economy-wide	0,35%	Colombia, n/a	Colombia, 5.3
Comoros	Absolute emission reduction	84%	2030	2030	Economy-wide	N/A		
Congo (Democratic Republic of)	Absolute emission reduction	17%	2000	2030	Economy-wide	0,27%		
Congo (Republic of)	Absolute emission reduction	48% and 55%	2000	2025 and 2035	Economy-wide	0,04%		
Cook Islands	Policies and actions	100% renewable energy share	2006	2020	Economy-wide	N/A		
Costa Rica	Relative emission reduction	44%	BAU	2030	Economy-wide	0,03%		
Côte d'Ivoire	Absolute emission reduction	28%	2012	2030	Economy-wide	0,06%		Côte d'Ivoire, n/a
Cuba	Policies and actions	Renewable energy share increase	N/A	2030	Sectoral	0,10%		
Djibouti	Absolute emission reduction	40% unconditional, 60% conditional	2000	2030	Economy-wide	N/A		
Dominica	Absolute emission reduction	17.9% by 2020; 39.2% by 2025; and 44.7% by 2030.	2014	2020, 2025 and 2030	Economy-wide	N/A		
Dominican Republic	Absolute emission reduction	25%	2010	2030	Economy-wide	0,08%		
Ecuador	Absolute emission reduction	9% unconditional, 20.9% conditional (for USCUSS sector, 4% unconditional, 20% conditional)	2010 (2008 for the US-CUSS sector)	2025	Economy-wide	0,14%		
Egypt	Policies and actions	N/A	N/A	2030	Economy-wide	0,66%		
El Salvador	Relative emission reduction	46% unconditional and 61% conditional	BAU	2025	Economy-wide	0,02%		
Equatorial Guinea	Absolute emission reduction	20%	2010	2030	Economy-wide	N/A		
Eritrea	Relative emission reduction	12% unconditional and 38.5 % conditional	2010	2030	Economy-wide	0,01%		
Ethiopia	Relative emission reduction	64%	BAU	2030	Economy-wide	0,31%		
European Union (EU)** The EU member States have submitted a joint INDC	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	8.97%	EU&Norway, 25.1	
Austria	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,17%	EU&Norway, 25.1	
Belgium	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,26%	EU&Norway, 25.1	
Bulgaria	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,12%	EU&Norway, 25.1	
Croatia	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,05%	EU&Norway, 25.1	
Cyprus	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,02%	EU&Norway, 25.1	
Czech Republic	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,26%	EU&Norway, 25.1	

Denmark	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,10%	EU&Norway, 25.1	Denmark, 26.9*
Estonia	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,04%	EU&Norway, 25.1	Estonia, 2.3
Finland	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,14%	EU&Norway, 25.1	Finland, 71.1*
France	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,92%	EU&Norway, 25.1	France, 51.1
Germany	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	1,86%	EU&Norway, 25.1	
Greece	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,20%	EU&Norway, 25.1	
Hungary	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,13%	EU&Norway, 25.1	
Ireland	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,13%	EU&Norway, 25.1	Ireland, 22.9
Italy	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,86%	EU&Norway, 25.1	
Latvia	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,03%	EU&Norway, 25.1	Latvia, 5.2
Lithuania	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,05%	EU&Norway, 25.1	
Luxembourg	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,02%	EU&Norway, 25.1	
Malta	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,00%	EU&Norway, 25.1	
Netherlands	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,41%	EU&Norway, 25.1	Netherlands, n/a
Poland	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,82%	EU&Norway, 25.1	Poland, 0.1
Portugal	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,14%	EU&Norway, 25.1	Portugal, 14.6
Romania	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,22%	EU&Norway, 25.1	
Slovakia	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,09%	EU&Norway, 25.1	
Slovenia	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,04%	EU&Norway, 25.1	Slovenia, 19.8
Spain	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,70%	EU&Norway, 25.1	Spain, 17.2; Catalonia, n/a
Sweden	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	0,13%	EU&Norway, 25.1	Sweden, 129.7
United Kingdom	Absolute emission reduction	At least 40%	1990	2030	Economy-wide	1,04%	EU&Norway, 25.2	UK, 23.5
Fiji	Relative emission reduction	30% CO2 emission reduction in the energy sector	BAU	2030	Economy-wide	N/A		
Gabon	Absolute emission reduction	At least 50%	2000	2025	Economy-wide	0,03%		
Gambia	Absolute emission reduction	44.4% and 45.4%	2010	2025 and 2030	Economy-wide	N/A		
Georgia	Relative emission reduction	15% unconditional and 25% conditional	BAU	2030	Economy-wide	0,03%		
Ghana	Relative emission reduction	15% unconditional, 45% conditional	BAU	2030	Economy-wide	0,08%		
Grenada	Absolute emission reduction	30% by 2025, 40% by 2030	2010	2025 and 2030	Economy-wide	N/A		
Guatemala	Absolute emission reduction	11.2% unconditional, 22.6% conditional	2005	2030	Economy-wide	0,07%		
Guinea	Absolute emission reduction	13%	1994	2030	Economy-wide	N/A		
Guinea-Bissau	Policies and actions	N/A	N/A	N/A	Economy-wide	N/A		
Guyana	Policies and actions	100% share of renewable energy	N/A	2025	Economy-wide	N/A		
Haiti	Relative emission reduction	5% unconditional, 26% conditional	BAU	2030	Economy-wide	0,03%		
Honduras	Relative emission reduction	15%	BAU	2030	Economy-wide	0,04%		
Iceland	Absolute emission reduction	40%	1990	2030	Economy-wide	0,01%		Iceland, 32.2
India	Carbon intensity reduction	33 to 35% carbon intensity reduction	2005	2030	Economy-wide	6,70%		
Indonesia	Relative emission reduction	29% unconditional, 41% conditional	BAU	2030	Economy-wide	1,93%		

Iran (Islamic Republic of)	Relative emission reduction	4% unconditional, 8% conditional	BAU	2030	Economy-wide	1,67%		
Iraq	Relative emission reduction	2% conditional and 13% unconditional	BAU	2035	N/A	0,49%		
Israel	Carbon intensity reduction	26%	2005	2030	Economy-wide	0,17%		
Jamaica	Relative emission reduction	7,80%	BAU	2030	Economy-wide	0,02%		
Japan	Absolute emission reduction	26%	2013	2030	Economy-wide	2,75%	Japan, n/a; Saitama, 6; Tokyo, 5.9	Japan, 2.6
Jordan	Relative emission reduction	14% (1.5% unconditional, 12.5% conditional)	BAU	2030	Economy-wide	0,06%		
Kazakhstan	Absolute emission reduction	15% unconditional - 25% conditional	1990	2030	Economy-wide	0,72%	Kazakhstan, n/a	
Kenya	Relative emission reduction	30%	BAU	2030	Economy-wide	0,16%		
Kiribati	Relative emission reduction	12.8% unconditional - 49% conditional	BAU	2030	Economy-wide	N/A		
Korea (Dem. People's Rep. of)	Relative emission reduction	40.25% (8% unconditional, 32.25% conditional)	BAU	2030	Economy-wide	0,12%		
Korea (Republic of)	Relative emission reduction	37%	BAU	2030	Economy-wide	1,41%	Korea, 22.9	
Kuwait	Policies and actions	INDC under analysis	N/A	2035	N/A	0,25%		
Kyrgyzstan	Relative emission reduction	11.49 to 13.75% unconditional - 29 to 30.89% conditional	BAU	2030	Economy-wide	0,04%		
Lao People's Dem. Rep.	Policies and actions	30% share of renewable energy in energy consumption	N/A	2020 and 2025	Economy-wide	N/A		
Lebanon	Relative emission reduction	15% unconditional - 30% conditional	BAU	2030	Economy-wide	0,06%		
Lesotho	Relative emission reduction	10% unconditional, 35% conditional	BAU	2030	Economy-wide	N/A		
Liberia	Relative emission reduction	10% by 2030, carbon neutrality by 2050	BAU	2030 and 2050	Sectoral	N/A		
Libya	N/A	INDC not submitted	N/A	N/A	N/A	0,14%		
Liechtenstein	Absolute emission reduction	40%	1990	2030	Economy-wide	N/A		Liechtenstein, 96.7
Macedonia	Relative emission reduction	30% unconditional, 36% conditional	BAU	2030	Economy-wide	0,02%		
Madagascar	Relative emission reduction	32%	BAU	2030	Economy-wide	N/A		
Malawi	Policies and actions	N/A	N/A	2030	Economy-wide	N/A		
Malaysia	Carbon intensity reduction	35% unconditional plus 10% conditional	2005	2030	Economy-wide	0,64%		
Maldives	Relative emission reduction	10% unconditional - 24% conditional	BAU	2030	Economy-wide	N/A		
Mali	Relative emission reduction	29% reduction for agriculture, 31% for energy and 21% for forests	BAU	2030	Economy-wide	N/A		
Marshall Islands	Absolute emission reduction	32% by 2025, 45% by 2030 - indicative target of 58% by 2035, net zero by 2050	2010	2025, 2030	Economy-wide	N/A		
Mauritania	Absolute emission reduction	22.3% (88% of which is conditional)	2010	2030	Economy-wide	N/A		
Mauritius	Relative emission reduction	30%	BAU	2030	Economy-wide	0,01%		
Mexico	Relative emission reduction	25% unconditional, 40% conditional	BAU	2030	Economy-wide	1,52%	Mexico, n/a	Mexico, 0.4-3
Micronesia (Federated States of)	Absolute emission reduction	28% unconditional, 35% conditional	2000	2025	Economy-wide	N/A		
Moldova (Republic of)	Absolute emission reduction	64/67% unconditional, 78% conditional	1990	2030	Economy-wide	0,02%		
Monaco	Absolute emission reduction	50%	1990	2030	Economy-wide	N/A		

Mongolia	Relative emission reduction	14%	BAU	2030	Economy-wide	0,09%	
Montenegro	Absolute emission reduction	30%	1990	2030	Economy-wide	0,00%	
Morocco	Relative emission reduction	42% (17% unconditional, 25% conditional)	BAU	2030	Economy-wide	0,17%	
Mozambique	Policies and actions	N/A	N/A	2030	Economy-wide	0,13%	
Myanmar	Policies and actions	30% increase in renewable energies	N/A	2030	Economy-wide	0,30%	
Namibia	Relative emission reduction	89%	BAU	2030	Economy-wide	0,03%	
Nauru	Policies and actions	N/A	N/A	2030	Economy-wide	N/A	
Nepal	Policies and actions	20% increase in renewable energies, 50% reduction in dependency to fossil fuels	N/A	2020 and 2050	Economy-wide	0,09%	
New Zealand	Absolute emission reduction	30%	2005	2030	Economy-wide	0,17%	
Nicaragua	N/A	INDC not submitted	N/A	N/A	N/A	0,04%	
Niger	Relative emission reduction	3.5% unconditional, 34.6% conditional	BAU	2030	Economy-wide	0,07%	
Nigeria	Relative emission reduction	20% unconditional and 45% conditional	BAU	2030	Economy-wide	0,66%	
Niue	Policies and actions	38% share of renewable energy unconditional, 80% conditional	N/A	2020 and 2025	Economy-wide	N/A	
Norway	Absolute emission reduction	40%	1990	2030	Economy-wide	0,14%	EU&Norway, 25.1
Oman	Relative emission reduction	2%	N/A	2030	Sectoral	0,21%	
Pakistan	Relative emission reduction	20%	BAU	2030	Economy-wide	0,84%	
Palau	Policies and actions	22% energy sector emissions reductions, 45% Renewable Energy, 35% Energy Efficiency	2005	2025	Economy-wide	N/A	
Palestine	Relative emission reduction	24.4% conditional; 12.8% unconditional	BAU	2040	Economy-wide	N/A	
Panama	Policies and actions	30% renewable energy target	2010	2050	Economy-wide	0,03%	
Papua New Guinea	Absolute emission reduction	Carbon neutrality	2010	2030	Economy-wide	N/A	
Paraguay	Relative emission reduction	10% unconditional and 20% conditional	BAU	2030	Economy-wide	0,08%	
Peru	Relative emission reduction	20% unconditional, 30% conditional	BAU	2030	Economy-wide	0,18%	
Philippines	Relative emission reduction	70%	BAU	2030	Economy-wide	0,41%	
Qatar	Policies and actions	N/A	N/A	2030	Sectoral	0,34%	
Russian Federation	Absolute emission reduction	25-30%	1990	2030	Economy-wide	4,56%	
Rwanda	Policies and actions	N/A	BAU	2030	Economy-wide	N/A	
Saint Kitts and Nevis	Relative emission reduction	22% by 2025, 35% by 2030	BAU	2025 and 2030	Economy-wide	N/A	
Saint Lucia	Relative emission reduction	16% by 2025 and 23% by 2030 (both conditional)	BAU	2025 and 2030	Economy-wide	N/A	
Saint Vincent and the Grenadines	Relative emission reduction	22%	BAU	2025	Economy-wide	N/A	
Samoa	Policies and actions	100% Renewable energy target	2007	2025	Sectoral	N/A	
San Marino	Absolute emission reduction	20%	2005	2030	Economy-wide	N/A	
Sao Tome and Principe	Absolute emission reduction	24%	2005	2030	Economy-wide	N/A	
Saudi Arabia	Relative emission reduction	up to 130 million tons of CO2 emission avoidance	N/A	2030	Sectoral	1,43%	

Senegal	Relative emission reduction	5% unconditional and 21%	BAU	2030	Economy-wide	0,04%		
Serbia	Absolute emission reduction	9,80%	1990	2030	Economy-wide	0,14%		
Seychelles	Relative emission reduction	21.4% and 29%	BAU	2025 and 2030	Economy-wide	N/A		
Sierra Leone	Peak of carbon emissions	Emissions will not exceed 7.58 MtCO2e	N/A	2035	Economy-wide	N/A		
Singapore	Carbon intensity reduction	36%	2005	2030	Economy-wide	0,12%		Singapore, 3.7
Solomon Islands	Absolute emission reduction	12% by 2025 and 30% by 2030	2015	2025 and 2030	Economy-wide	N/A		
Somalia	Policies and actions	N/A	N/A	N/A	Sectoral	N/A		
South Africa	Peak of carbon emissions	Emissions peak between 398 and 614 Mt CO2–eq	N/A	2025 and 2030	Economy-wide	1,14%		South Africa, n/a
South Sudan	Policies and actions	N/A	N/A	2030	Sectoral	0,00%		
Sri Lanka	Relative emission reduction	7% unconditional, 23% conditional	BAU	2030	Economy-wide	0,08%		
Sudan	Policies and actions	20% renewable energy target	BAU	2030	Sectoral	0,32%		
Suriname	Policies and actions	Above 25% of renewable energies by 2025 plus forestry commitments	N/A	2025	Economy-wide	0,01%		
Swaziland(Eswatini)	Policies and actions	100% increase of renewable energy share	2010	2030	Economy-wide	N/A		
Switzerland	Absolute emission reduction	35% by 2025, 50% by 2030	1990	2025 and 2030	Economy-wide	0,11%	Switzerland, 5.2	Switzerland, 96.7
Syria	N/A	INDC not submitted	N/A	N/A	N/A	0,09%		
Tajikistan	Absolute emission reduction	80-90% unconditional - 65-75% conditional	1990	2030	Economy-wide	0,03%		
Tanzania (United Republic of)	Relative emission reduction	10-20%	BAU	2030	Economy-wide	0,19%		
Thailand	Relative emission reduction	20% unconditional and 25% conditional	BAU	2030	Economy-wide	0,83%	under consideration	under consideration
Timor-Leste (East Timor)	Policies and actions	N/A	N/A	N/A	Economy-wide	N/A		
Togo	Relative emission reduction	11.14% unconditional, 31.14% conditional	BAU	2030	Economy-wide	0,02%		
Tonga	Policies and actions	50% of renewable energy share	N/A	2020	Economy-wide	N/A		
Trinidad and Tobago	Relative emission reduction	15%	BAU	2030	Economy-wide	0,13%		
Tunisia	Carbon intensity reduction	41% carbon intensity (13% unconditional, 28% conditional)	2010	2030	Economy-wide	0,08%		
Turkey	Relative emission reduction	21%	BAU	2030	Economy-wide	1,07%	Turkey, n/a	
Turkmenistan	Absolute emission reduction	Stablisation of greenhouse gas emissions	2000	2030	Economy-wide	0,25%		
Tuvalu	Absolute emission reduction	60% economy wide, 100% from electricity generation sector	2010	2025	Economy-wide	N/A		
Uganda	Relative emission reduction	22% reduction of GHG in 2030 as compared to BAU	BAU	2030	Economy-wide	N/A		
Ukraine	Absolute emission reduction	40%	1990	2030	Economy-wide	0,62%	Ukraine, n/a	Ukraine, 0.4
United Arab Emirates	Policies and actions	Increase of clean energy to 24%	N/A	2021	Sectoral	0,48%		
United States of America (USA)	Absolute emission reduction	26-28%	2005	2025	Economy-wide	12,91%	California, 15.7; Massachusetts, n/a, Virginia, n/a; Washington, n/a	

Uruguay	Carbon intensity reduction	24% (CO2), 57% (CH4) and 48% (N2O)	1990	2025	Economy-wide	0,10%	
Uzbekistan	Absolute emission reduction	10%	2010	2030	Economy-wide	0,34%	
Vanuatu	Relative emission reduction	100% reduction for the power sector, 30% reduction for the energy sector as a whole	BAU	2030	Economy-wide	N/A	
Venezuela	Relative emission reduction	20%	BAU	2030	Economy-wide	0,52%	
Viet Nam	Relative emission reduction	8% unconditional - 25% conditional	BAU	2030	Economy-wide	0,69%	Vietnam, n/a
Yemen	Relative emission reduction	1% unconditional, 13% conditional	BAU	2030	Sectoral	0,08%	
Zambia	Absolute emission reduction	25% unconditional, 47% conditional	2010	2030	Economy-wide	0,13%	
Zimbabwe	Carbon intensity reduction	33% carbon intensity reduction	BAU	2030	Economy-wide	0,06%	

Source: IGES NDC database, Version 6.3, April 2019; IEA 2018; World Bank Carbon Pricing Dashboard
Note: Nominal prices, February 2019. Prices are not necessarily comparable between countries and initiatives as numbers of sectors covered and allocation methods applied differ.
(*) indicates strong sector limitation, reported to WB dashboard.