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of the Christian- Albrechts-Universität Kiel

**Modelling of agriculture and climate policies: Impacts of
cooperation on sustainability and economic growth**

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List of Abbreviations

AEEI	Autonomous Energy Efficiency
AER	Absolute Error Ratio
APEC	Asia-Pacific Economic Cooperation
BAU	Business as Usual
BCA	Border Carbon Adjustment
CAGR	Constant Annual Growth Rate
CDM	Clean Development Mechanism
CE	Cross Entropy
CES	Constant Elasticity of Substitution
CGE	Computable General Equilibrium
CO ₂	Carbon dioxide
COP	Conference of Parties
CORSIA	Carbon Offsetting and Reduction Scheme for International Aviation
DART	Dynamic Applied Regional Trade
DART-CLIM	Dynamic Applied Regional Trade-Climate
DOE	Design of Experiment
EITE	Energy Intensive and Trade Exposed
EMF	Energy Modelling Forum
ETS	Emissions Trading Scheme
EU	European Union
FFS	Fossil Fuel Subsidies
G20	Group of Twenty
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GME	Generalized Maximum Entropy
GTAP	Global Trade Analysis Project
HEV	Hicksean Equivalent Variation
HPD	Highest Posterior Density
I/O	Input-Output

IAM	Integrated Assessment Models
IEA	International Energy Agency
IEO	International Energy Outlook
IMO	International Maritime Organization
IQR	Inter-Quartile Range
JI	Joint Implementation
LHS	Latin Hypercube Sample
LULUCF	Land-Use, Land-Use Change and Forestry
MAC	Marginal Abatement Costs
MRA	Meta-Regression Analysis
NC-GHG	Non-CO ₂ Greenhouse Gases
NDC	Nationally Determined Contributions
ODA	Oversees Development Aid
OECD	Organization for Economic Co-operation and Development
R&D	Research and Development
RMSE	Root Mean Square Error
SAM	Social Accounting Matrix
SO	Simulation Optimization
SSA	Systematic Sensitivity Analysis
ToT	Terms of Trade
USD	United States Dollar
WEO	World Energy Outlook
WTO	World Trade Organization

Abstract

This dissertation quantifies the economic and environmental impacts of different climate policy regimes using ex-ante modelling, with a focus on cooperative policies. The thesis makes a significant methodological contribution by developing a Bayesian calibration method for reference scenarios in dynamic computable general equilibrium (CGE) models and important empirical contributions with the modelling and analysis of the impacts of climate policies in the context of the Paris Agreement.

Using the CGE model, DART, we examine several aspects in more detail. (1) We disaggregate the global costs of regional carbon markets into the direct costs (via the domestic market) and the indirect costs (via international spillover effect). (2) We model different variants for designing a joint carbon market between the EU and China by varying the share of tradable permits, the amount of transfer payments from the EU to China, and the extent of trade barriers. (3) We investigate the extent of carbon leakage through the EU ETS. Mainly, we analyse the effect of structural (flexibility in the electricity grid), technological (advances in renewables), political (binding targets in non-ETS sectors), and behavioural factors (flexible consumer adjustment to energy price changes) on emissions leakage to non-regulated regions. (4) Finally, we model a global ETS with an allocation of allowances proportional to population share, and the associated monetary transfers are analysed. (5) Using meta-regression analysis (MRA) based on 15 different models, we examine how regional and sectoral disaggregation, endogenous technological change is modelled, and different databases for trade elasticities affect the model results.

Some key results are as follows. (1) Our results show that both policy design and the CGE model framework affect mitigation costs. A globally harmonised CO₂ price could reduce the mitigation costs of achieving Nationally Determined Contributions (NDCs) by two-thirds compared to non-cooperative climate policies. (2) Regional CO₂ markets can also reduce costs, but the savings achieved are smaller, and the regional cost incidence varies widely. (3) The dynamics of the reference scenario and the structural features of a CGE model also affect cost estimates. (4) A joint ETS between China and EU has higher benefits for EU. (5) Intersectoral carbon leakage in the EU is lowest with emission reduction targets in unregulated sectors. (6) Technological advancement of renewables lowers the EU ETS allowance price and mitigates inter-sectoral and international carbon leakage.

However, CGE models do not account for some critical practical challenges in implementing climate policy. For example, they do not consider legal (compatibility with WTO rules), political economy (influence of lobby groups), practical (costs of monitoring, reporting, and verifying an ETS) challenges in the analysis. A promising way to compensate for some of these weaknesses is to extend CGE models to include political economy factors. In addition, we propose to use econometric estimation methods in calibrating the models to improve the robustness of the results derived from the CGE models.

Zusammenfassung

In dieser Dissertation werden die wirtschaftlichen und ökologischen Auswirkungen verschiedener klimapolitischer Regime anhand von Ex-ante-Modellierung quantifiziert, wobei der Schwerpunkt auf kooperativen Politikmaßnahmen liegt. Die Arbeit leistet einen wichtigen methodischen Beitrag durch die Entwicklung einer Bayesian Kalibrierungsmethode für Referenzszenarien in dynamischen berechenbaren allgemeinen Gleichgewichtsmodellen (Computable General Equilibrium, CGE) und einen wichtigen empirischen Beitrag mit der Modellierung und Analyse der Auswirkungen der klimapolitischen Maßnahmen im Kontext des Pariser Abkommens.

Mithilfe des CGE-Modells, DART, untersuchen wir verschiedene Aspekte genauer. (1) Wir disaggregieren die globalen Kosten regionaler Kohlenstoffmärkte in die direkten Kosten im heimischen Markt und die internationalen Spillover-Effekte in unbeteiligte Regionen. (2) Wir modellieren verschiedene Varianten für die Ausgestaltung eines gemeinsamen Kohlenstoffmarktes zwischen der EU und China; dabei wird der Anteil handelbarer Zertifikate, die Höhe der Transferzahlungen der EU an China und das Ausmaß der Handelshemmnisse variiert. (3) Wir untersuchen das Ausmaß der Verlagerung von CO₂-Emissionen durch das EU-ETS (carbon leakage). Der Effekt struktureller (Flexibilität im Stromnetz), technologischer (Fortschritte im Bereich der erneuerbaren Energien), politischer (verbindliche Ziele in den Nicht-ETS-Sektoren) und verhaltensbezogener Faktoren (flexible Anpassung der Verbraucher an Energiepreisänderungen) auf die Verlagerung der Emissionen in nicht-regulierte Regionen wird analysiert. (4) Schließlich wird ein globales ETS mit einer Zuteilung der Zertifikate proportional zum Bevölkerungsanteil modelliert und die damit verbundenen monetären Transfers analysiert. (5) In einer Meta-Regressionsanalyse (MRA) basierend auf 15 verschiedenen Modellen wurde zum Beispiel untersucht wie die jeweilige regionale und sektorale Disaggregation, die Art der Modellierung des endogenen technologischen Wandels und die Verwendung unterschiedlicher Datengrundlagen für die Handelselastizitäten die Modellergebnisse beeinflussen.

Unsere Ergebnisse zeigen, (1) dass sowohl die Gestaltung der Politikmaßnahmen als auch der CGE-Modellrahmen die Mitigationskosten beeinflussen. Ein global harmonisierter CO₂-Preis könnte die Vermeidungskosten für das Erreichen der national festgelegten Beiträge (Nationally Determined Contributions, NDCs) um zwei Drittel im Vergleich zu nicht-kooperativer Klimapolitik senken. (2) Auch regionale CO₂-Märkte können die Kosten senken, aber die erzielten

Einsparungen sind geringer und die regionale Verteilung der Kosten ist sehr unterschiedlich. (3) Aber auch die Dynamik des Referenzszenarios und die strukturellen Merkmale eines CGE-Modells beeinflussen die Kostenschätzungen. (4) Ein gemeinsamer Emissionshandel zwischen China und der EU hat einen höheren Nutzen für die EU. (5) Carbon leakage aus dem europäischen Emissionshandel ist am geringsten, wenn Emissionsreduktionsziele in nicht regulierten Sektoren gelten. (6) Der technologische Fortschritt bei den erneuerbaren Energien senkt den Preis für Emissionszertifikate der EU und mindert carbon leakage zwischen den Sektoren und Ländern.

In CGE-Modellen werden allerdings einige wichtige praktischen Herausforderungen bei der Umsetzung von Klimapolitik nicht berücksichtigt. Die Kosten für die Überwachung, Berichterstattung und Überprüfung eines ETS werden nicht erfasst. Auch Fragen der politischen und rechtlichen Machbarkeit, wie der Einfluss von Lobbygruppen oder die Vereinbarkeit mit den WTO-Regeln können nicht adressiert werden. Ein vielversprechender Weg einige dieser Schwächen auszugleichen ist die Erweiterung von CGE-Modellen um polit-ökonomische Faktoren. Zudem schlagen wir vor ökonometrische Schätzmethoden bei der Kalibrierung der Modelle einzusetzen, um die Robustheit der aus den CGE-Modellen abgeleiteten Ergebnisse zu verbessern.

1. Introduction

Climate change is a global challenge and anthropogenic activities have already caused about 1-degree of global warming since pre-industrial levels and will continue to do so in the future (IPCC 2018). This is concerning since there is a direct link between increase in global temperature and increase in frequency and severity of climate and weather extremes (IPCC 2021). Climate change could also have economic impacts by hindering growth and development globally, though with regional and sectoral differences in terms of severity of damages (Stern 2006, 2008; Tol 2009; Dell et al. 2012).

Climate strategy consists of both mitigation and adaptation. Climate change mitigation directly addresses the core problem which is rising Greenhouse Gas (GHG) emissions and therefore, mitigation comprises of actions that would reduce the total global GHG emissions (e.g., switching from highly carbon-intensive energy sources to less-carbon intensive or carbon-neutral sources, improving energy efficiency, better land use and restoration etc.). Climate change adaptation, on the other hand, covers countries' actions to setup systems and societies that can withstand the impacts of climate change (e.g., investments in public infrastructure like dams, technological progress in developing in climate resistant inputs for agriculture etc.). Naturally, both mitigation and adaptation (Bruin et al. 2009; Chambwera et al. 2014; Fankhauser 2010) efforts entail costs and benefits which makes them of interest to policymakers globally.

For almost three decades, the annual Conference of the Parties (COP) meetings have provided a crucial platform for the establishment of some of the most important global climate agreements starting from the adoption of the Kyoto Protocol in 1997 to that of the Paris Agreement in 2015. Historically, at the COPs international climate negotiations have been set-up as top-down (e.g., in the Kyoto Protocol) or bottom-up (e.g., in the Paris Agreement) discussions and each one of these approaches has its own share of advantages and challenges (Green et al. 2014). Nevertheless, a common characteristic of the climate negotiations is that in the end, irrespective of whether the agreement is accepted via a top-down or a bottom-up style, the adopting Parties have an emission reduction goal that they are required to fulfil within a defined commitment period.

Typically, countries use a policy-mix to reach a GHG emissions reduction target. Some of the prominent policies that have been historically used by countries are carbon taxes, emissions trading schemes, support for R&D to improve energy efficiency and adoption of clean energy sources. Since early 2000s, there has been an upward trend in the number of carbon pricing instruments implemented globally. In 2021, about 21.5% of global GHG emissions are being priced with 64 carbon pricing instruments worldwide (World Bank 2021).

Expectedly, ex-ante impact evaluations of proposed policies are necessary to assess their potential economic and environmental impacts. Outcomes of these evaluations play a role in shaping the final decision of policymakers regarding the adoption of policies. Computable General Equilibrium (CGE) models are extensively used by public and private actors to perform ex-ante evaluations. CGE models capture the economy-wide interlinkages between different sectors, regions and agents. The strength of the method lies in the ability of the model to capture direct and indirect multiplier effects, both domestic and international, of a policy in question. In the past, CGE models have been used for ex-ante assessments of trade policy (Melo 1988; Nilsson 2018), climate policy and energy policy (Babiker et al. 2003; Böhringer et al. 2009). The application of CGE models for the assessment of climate policies gained popularity since the 1990s (Bergman 1988, 2005). Moreover, to improve comparability across results from different CGE models over time multi-model comparisons with CGE models also became common and cross-modelling exercises with CGE models have been conducted for assessing the costs of the Kyoto Protocol (Weyant 1999) and the Paris Agreement (Böhringer et al. 2021).

This dissertation focusses on the economic costs of climate change mitigation policies with a focus on multilateral and cooperative climate change policy architectures (Page 13, Stavris et al. 2014). Inclusion of collaboration measures was part of the Kyoto Protocol with the development of Clean Development Mechanisms (CDM) and Joint Implementation (JI). Using the flexibility of CDM and JI, countries were allowed to carry out part of their mitigation through initiatives in other countries. Similarly, Article 6 of the Paris Agreement encourages voluntary cooperation between regions towards successfully reaching the NDC targets and in this dissertation, we explore several instruments of coordination that countries could voluntarily deploy.

The individual chapters of this dissertation advance the existing CGE literature by making methodological contributions as well as specific policy assessments. Chapter 2 to Chapter 4 adds

to the wide-ranging CGE literature by contributing a systematic review on cooperative and coordinated climate change policy architectures, providing a quantitative meta-regression analysis and proposing a novel method for calibration of dynamic CGE models. Subsequently, each one of Chapter 5 to Chapter 7 model a variety of multilateral and bilateral cooperative strategies for implementation of mitigative climate policies.

Chapter 2 provides a detailed review of the literature on carbon pricing and the economic gains that could be achieved by cooperation and coordination. In this review we collect and categorise data on scenarios from 59 studies that use CGE and Integrated Assessment Models (IAM), including 6 meta-analysis and multi-model comparisons, into five instruments of cooperation and coordination. These include – (1) globally harmonized carbon prices, (2) multilateral fossil fuel subsidy reform, (3) international sectoral agreements, (4) extending coverage of carbon pricing across sectors and GHG other than CO₂ and (5) coordinating in mechanisms against carbon leakage. The key results from modelling literature on carbon pricing in the last two decades are succinctly summarised.

Chapter 3 offers a meta regression analysis (MRA) for understanding why there are wide range of estimates for MACs across models even when assessing the same policy. In this chapter, we use outputs from 15 CGE models that participated in a harmonized cross-model comparison study to understand the role of structural model features and policy features in determining marginal abatement cost (MAC) estimates from CGE models. We consider six structural features of models as explanatory variables along with two categorical variables for policy targets and design. The policy target that was modelled by the 15 models the unconditional and conditional Nationally Determined Contributions (NDCs) (UNFCCC 2015) and a 2-degree coherent target. We run regressions at the global level and for 14 regions for which all the models reported their outcomes. Thus, we employ the MRA tool to quantitatively combine results from several models to provide robust insights that are richer than results from a single model.

Chapter 4 provides a methodological contribution towards improving the baseline calibration of dynamic CGE models using Bayesian estimation. Baseline calibration of CGE models is important since the policy analysis is conducted using the baseline model outputs as the reference. Despite the critical role that calibration of dynamic baseline plays, the calibration approaches used by CGE modelers are often not clearly stated and the calibration process remains quite opaque to a non-

expert in the field. To improve the status quo, we propose a novel and replicable Bayesian framework for baseline calibration of dynamic CGE models consisting of metamodel-based simulation optimization. An application of the framework is shown using the Dynamic Applied Regional Trade (DART) model by calibrating 120 model outputs using 1500 input parameters. To showcase the method and the policy relevance of baseline calibration and the ensuing baseline dynamics, we model a policy for evaluating the regional MACs and assess the policy impact relative to the baseline calibrated using our proposed method versus to a conventionally calibrated baseline. Our results show that baseline calibration certainly impacts the policy implications that are derived and thus, more openness is needed in the calibration methods.

Chapter 5 analyses the global costs of fulfilling the (initial) conditional NDC pledges under different levels of cooperation and permit allocation principles. This chapter uses the DART model to analyse the economic costs that regions would face when countries implement unilateral carbon prices (scenario REG) as compared to when countries introduce globally harmonized prices via an international Emissions Trading Scheme (ETS). Furthermore, we model two different permit allocation rules in the global ETS. In the first allocation scenario (scenario GLOB), annual regional permit endowments are aligned with the regional NDC pathway. Different from this, the second allocation principle (scenario PERCAP) follows a carbon egalitarian approach and thus, the global CO₂ budget consistent with the NDC pledges is distributed across regions in proportion to regional population shares. Furthermore, we also disaggregate the regional welfare effects into the direct component (i.e. direct mitigation costs of CO₂) and indirect costs (i.e. international spillover effects). Our results show global welfare losses are the least in PERCAP followed by GLOB and REG, respectively. The regional welfare losses are reduced in GLOB as compared to REG and the regions that gain in welfare in REG continue to do so in GLOB though with lower levels. Within the fossil energy-exporting regions, the dominant channel of welfare loss is the indirect costs which they face due to a fall in demand for carbon-intensive energy sources. When the regional permit allocation in a global ETS has underpinnings in carbon egalitarianism, monetary transfers, comparable to the per capital official development aid (ODA), would be needed from developed regions to the developing regions.

Chapter 6 focuses on the economic impacts of linking the European and Chinese ETS in the presence of unilateral climate policy that is aligned with the NDC pledges. The impacts of linking

are analysed with different assumptions about the following three factors – (1) share of allowances traded between EU and China, (2) bilateral transfer payments and (3) ease of commodity trade. The DART model is again used for the quantitative analysis. Our results show that EU maximizes welfare gains with unrestricted permit trade while China’s welfare is maximized when only half of the permits are traded. Even with bilateral transfer payments, wherein the EU (or China) faces a higher (or lower) emission reduction target, China is not sufficiently economically compensated such that fully linked ETS becomes attractive for China. With increase in ease of commodity trade, gains associated with linking increase for China but reduce for the EU. Overall, gains in EU and China are heterogenous and from our scenarios we do not identify a single scenario where the economic gains for both EU and China would be maximized. Additionally, economic impacts within EU are also very varied and therefore, if the EU and China choose to link their ETSs the EU would also have to establish some internal compensation schemes.

Chapter 7 investigates the interlinkages between the EU ETS and policies supporting technological advancement in renewables, hindrance in grid-integration, flexible consumer preferences and effort sharing agreement. Unlike in Chapter 5 and Chapter 6, this analysis is conducted with a static version of DART. From our results we see that intersectoral carbon leakage is lower with higher learning in renewable electricity technologies and flexibility in the electricity grid. Increase in the EU ETS allowance price should be accompanied with policies in non-ETS sectors to avoid inter-sectoral carbon leakage in the EU. International policy context also matters. A higher allowance price in the EU-ETS does not necessarily shift consumer decisions towards emission free alternative (for e.g., in mobility and heating) since this is accompanied by low international prices of fossils. Lastly, there are differences in the energy portfolios within the EU with some countries being more coal-dependent than others. This difference in the energy portfolio leads to unequal abatement efforts with the EU regions which is also important to consider for a just transition within the EU.

1.1 Publication bibliography

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2. **The economic and environment benefits from international coordination on carbon pricing: A review of economic modelling studies¹**

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Abstract

This paper reviews quantitative estimates of the economic and environmental benefits from different forms of international coordination on carbon pricing based on economic modelling studies. Forms of international coordination include: harmonising carbon prices (e.g., through linking carbon markets), extending the coverage of pricing schemes, phasing out fossil fuel subsidies, developing international sectoral agreements, and establishing coordination mechanisms to mitigate carbon leakage. All forms of international cooperation on carbon pricing could deliver benefits, both economic (e.g., lower mitigation costs) and environmental (e.g., reducing greenhouse gas (GHG) emissions and carbon leakage). There is scope to considerably increase the coverage of carbon pricing, since until 2021 only around 40% of energy-related CO₂ emissions in 44 OECD and G20 countries face a carbon price. There is also significant scope to improve international coordination on carbon pricing: moving from unilateral carbon prices to a globally harmonized carbon price to reach the first round of NDC targets for 2030 can reduce global mitigation cost on average by two thirds or \$229 billion. Benefits tend to be higher with broader participation of countries, broader coverage of emissions and sectors and, more ambitious policy goals. Extending carbon pricing to non-CO₂ GHG could reduce global mitigation costs by up to 48%. Absolute cost savings from harmonized carbon prices increase by almost 70% in 2030 for reductions in line with the 2°C target. Most, but not all, countries gain economic benefits from international cooperation, and these benefits vary significantly across countries and regions.

¹ The article in this chapter was also published online as a non-peer-reviewed OECD Working Paper 173 (working paper) in 2021. Retrievable under: https://www.oecd-ilibrary.org/environment/the-economic-and-environmental-benefits-from-international-co-ordination-on-carbon-pricing_d4d3e59e-en

Complementary measures outside cooperation on carbon pricing (e.g., technology transfers) could potentially ensure that cooperation provides economic benefits for all countries.

Keywords: Co-operation, Climate change mitigation, Harmonizing carbon pricing, Fossil fuel subsidy reforms, Border carbon adjustment, Greenhouse gas mitigation, Sectoral agreements, Climate-economy modelling

2.1 Introduction

Global climate action needs to increase substantially to limit global warming to ‘well-below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels’ as per the target of the Paris Agreement (UNFCCC, 2015). Yet, the aggregate emission reductions associated with countries’ initial unconditional Nationally Determined Contributions (NDCs) would imply a 66% chance to only limit warming to 3.2°C by the end of the century (UNEP 2019). The NDC updates that several countries have made by mid-2021 are still expected to lead to global warming of more than 2°C (CAT 2021) though (Höhne et al. 2021) show that globally the 2°C target might be within reach if the national net-zero targets are implemented.

Pricing carbon dioxide (CO₂) and other greenhouse gas (GHG) emissions through emissions trading schemes (ETSs) or taxes is a key element of an economically efficient climate strategy. It incentivises private and public actors to reduce emissions cost-effectively while spurring innovation into zero-carbon technologies. Carbon pricing has also important synergies with broader well-being goals, enhancing public health through lower levels of air pollution while generating revenues that allow for an increase in public investments or reducing distortionary taxes (OECD 2019). Yet, carbon pricing alone is not sufficient to trigger the scale and speed of the economic transformations needed to reach the temperature goals of the Paris Agreement but needs to be accompanied by complementary policies (innovation, information provision, etc.) (Tvinnereim and Mehling 2018; Stiglitz 2019, 2019, 2019). Indeed, carbon pricing so far has had only limited effects on aggregate emission reductions (Green 2021).

While the number of national and sub-national carbon pricing schemes has increased from 16 to 64 between 2009 and 2021 (World Bank, 2021), around 60% of energy-related CO₂ emissions in 44 OECD and G20 countries do not face a carbon price (OECD 2021a). Indeed, only 3.8% of global emissions are priced above USD 40 per ton of CO₂ – a low-end estimate for carbon prices necessary in order to meet the goals of the Paris Agreement (OECD 2021a; World Bank 2021).

International cooperation especially but not limited to harmonized carbon pricing in a broader sense, and on meeting individual countries’ emissions reduction targets is expected to bring important economic (e.g. reduce climate policy costs, fiscal revenues from allowance sales), environmental (e.g. reducing GHG emissions and air pollution emissions as well as carbon

leakage) benefits) and political benefits (e.g., signalling a commitment to climate mitigation to domestic and foreign stakeholders) that could potentially enhance the ambition of cooperating countries (Nachtigall 2019). Combining these benefits – for example reinvesting the savings in mitigation costs into additional mitigation or energy efficiency measures - could significantly enhance global mitigation ambition. International climate agreements have explicitly enshrined mechanisms to foster international cooperation, including in Article 6 of the Paris Agreement. Yet, evidence on the economic and environmental benefits of international cooperation is scarce and scattered. Quantifying the benefits of international coordination especially on pricing of GHG emissions, including carbon dioxide (CO₂) and the distribution of these benefits across country groupings can help policy makers make better-informed decisions about the implications and potential forms of international coordination.

This review provides a comprehensive overview of the economic and environmental benefits of a variety of forms of cooperation between countries, mainly based on economic modelling studies that can provide quantitative estimates.

2.2 Methods

This paper synthesises estimates of the economic and environmental benefits of international cooperation based on the economic modelling literature mostly from the past 10 years. We conducted the literature search on Google Scholar and Web of Science as the main search engines due to their vast scope and easy accessibility. On a couple of occasions, we used ECONIS to supplement our literature search. ECONIS is the online catalogue of the ZBW – German National Library of Economics – Leibniz Information Centre for Economic, which broadly collects economic literature and includes all major economic journals and grey literature from all major institutions undertaking economic research. We applied three general criteria for selecting studies (dominantly peer-reviewed studies and some reports and working papers from OECD, IEA, and conference papers)

1. We only consider studies that use **ex-ante** policy analysis methods. This literature typically uses numerical modelling techniques, particularly IAMs and CGE models (See Annex 1 for an overview of these modelling methods) to quantify the socio-economic and/or

environmental effects of climate policies². Therefore, we focus only on studies that use either of these models.

2. We only consider studies that provide quantitative **estimates of economic costs** measured either as a carbon price, GDP changes or welfare changes (mostly in terms of Hicksian-Equivalent Variation – HEV).
3. We focus on review studies with a **multi-regional or global** focus and therefore exclude articles that use a single country model. This criterion is needed because the goal of our study is to synthesise economic and environmental gains of cooperation and models need to have a multi-regional or fully global representation of countries to simulate cooperation between regions. Only in very few cases where sufficient multi-regional evidence was missing have we included single-country studies.

In addition to these three general criteria, specific search terms were used to select studies for each of the sections (see Table 2.1). Particularly, our study reviews five independent instruments for initiating coordinated and cooperative action between countries. These are harmonising carbon prices (e.g., through linking carbon markets), extending the coverage of pricing schemes, phasing out fossil fuel subsidies, developing international sectoral agreements, and establishing coordination mechanisms to mitigate carbon leakage.

Table 2.1: List of keywords used in literature search

Section 2.3 Harmonising carbon prices	Paris Agreement, Nationally Determined Contributions, Intended Nationally Determined Contributions	+	Integrated Assessment, General Equilibrium	+	Abatement Cost, Mitigation cost		
Section 2.4 Extending the coverage of pricing schemes	Sectoral Agreements, Sectoral Coverage	+	Integrated Assessment, General Equilibrium	+	Abatement Cost, Mitigation cost	+	Multigas mitigation
Section 2.5 Multilateral fossil fuel subsidy reform		+	Integrated Assessment, General Equilibrium	+	Abatement Cost, Mitigation cost	+	Fossil Fuel Subsidy

² Political benefits are hard, if not impossible, to quantify.

Section 2.6 International sectoral reforms	Sectoral Agreements	+	Integrated Assessment, General Equilibrium	+	Abatement Cost, Mitigation cost		
Section 2.7 Coordination mechanism for mitigating carbon-leakage	Border Carbon Adjustment, Border Carbon	+	Integrated Assessment, General Equilibrium	+	Abatement Cost, Mitigation cost	+	Carbon Leakage

Section 2.3 focuses on price harmonization and so in this section we only selected studies that report the cost estimates for the most recent emission targets i.e. the initial NDC pledges submitted by countries under the Paris Agreement. We went through the results from these searches and selected only those studies that met the three general criteria and modelled scenarios with both unilateral prices and harmonized prices. Additionally, few papers (Springer 2003) focusing on the agreements passed in accordance with the previous Conference of Parties (COPs) were looked at to supplement the full scope of the global climate change debate. For Section 2.4 to Section 2.7, topic-wise literature searches were done to expand the study to include these other four coordination instruments.

A snowball approach followed the first step of systematic identification of studies. This step included identifying literature from the reference list of the relevant studies found via the search engines. The final tally of 59 studies included in our study is supported by the literature search and the authors' experience. Table 2.2 gives an overview of the number of studies considered in each section. In addition, we include two meta-analyses (Branger and Quirion 2014; Kuik et al. 2009) and two cross-model comparison studies (Böhringer et al. 2021a; Weyant et al. 2006). Therefore, the papers that are included within these four meta-analyses are not separately included in our review unless they provide unique insights.

This paper is structured as follows. Sections 2.3 and 2.4 focus on carbon pricing and discuss the benefits of harmonizing carbon prices across countries and extending the scope of carbon pricing, respectively. Section 2.5 deals with international cooperation in phasing out fossil fuel subsidies which act as negative carbon prices and section 2.6 with international sectoral agreements. Finally, section 2.7 discusses options to address carbon leakage if international harmonization of climate policy fails. Finally, Section 2.8 provides a conclusion.

Table 2.2: Publications included in this paper

Section	Name	Number of studies	Publication year of latest study
2.3	Benefits of harmonizing carbon prices	24	2021
2.3.1	Global cooperation	14 ^b	2021
2.3.2	Regional cooperation	10 ^b	2021
2.4	Extending coverage of carbon pricing schemes	11	2019
2.4.1	Extending sectoral coverage	8	2019
2.4.2	Extending GHGs	3 ^{a,b}	2012
2.5	Multilateral Fossil fuel subsidy reform	6	2021
2.6	International sectoral agreements	2	2012
2.7	International coordination on mitigating carbon leakage	16	2018
2.7.1	Environmental effects	13 ^{a,b}	2018
2.7.2	Economic effects	13 ^{a,b}	2018
2.7.3	Strategic incentives to join climate coalitions	3	2016
Total		59	

Note: The superscripts ^a and ^b indicate that the sections include a meta-analysis or a multi-model study, respectively. Source: Authors.

2.3 Benefits of Harmonising carbon prices

International climate agreements have explicitly enshrined mechanisms to foster international cooperation, including most recently via Article 6 of the Paris Agreement. This section reviews the economic and environmental benefits of global (Section 2.3.1) cooperation, largely focussing on, but not limited to the goals of the Paris Agreement, and the benefits of regional cooperation (Section 2.3.2).

Flexibility in the location of mitigation efforts allows for increased mitigation in countries with low abatement costs and reduced mitigation in countries with high abatement costs, achieving the aggregate emission target at a lower cost. A uniform global carbon price would, in theory, ensure that the resulting emission reductions are reached with the lowest global economic cost, regardless of whether the global price is implemented through uniform national carbon taxes (and transfer mechanism), a global ETS or full linking of national ETS (Baranzini et al. 2017). Sub-global harmonisation of carbon prices could only realise some of the economic benefits. Assessing the economic and environmental benefits from harmonised carbon prices requires a comparison of achieving a specific target unilaterally (e.g., meeting NDC pledges) with achieving the same target

jointly. The aggregate cost of reaching both national and international emission reduction targets depend on four main drivers (Peterson and Weitzel 2015):

- The stringency of emission targets relative to the business-as-usual (BAU) scenario.
- The national abatement costs which are dependent on the emission intensity of production and consumption patterns, the sectoral composition of economies and technology costs.
- National and international feedback effects of climate policy through changes in relative prices of fossil energy which affect energy markets and input prices with implications on (inter)national value chains, production and consumption of other goods.
- The level of international cooperation as this could harmonise abatement costs across different sources and locations, and for some countries could also generate fiscal income from allowance trading if there are international carbon markets.

Several caveats need to be kept in mind when comparing different modelling studies.

- Different models assume different economic structures for countries and regions and make a range of different assumptions on the above-mentioned drivers.
- Quantifying mitigation pledges is not straightforward for NDCs that are not expressed as absolute emission reductions. Additional assumptions are necessary for pledges made with emissions intensity targets, emission reductions relative to pre-specified baseline emissions or for different target years (2025 or 2030).
- Translating international goals related to specific temperature targets into national emission reduction targets is even more challenging in the absence of a globally agreed burden sharing agreement.³

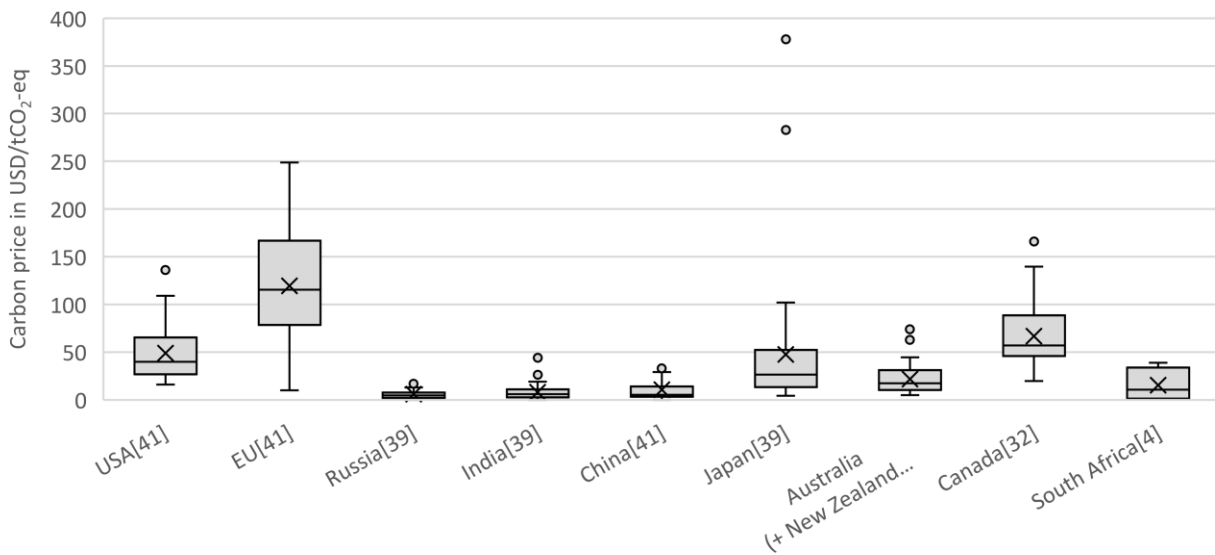
Results presented here focus on aggregate results for a particular country or region; the impact for individual actors within a country or region could be significantly different from the aggregate average.

2.3.1 Global Harmonisation of carbon prices

³ Researchers typically analyze a number of burden-sharing rules to determine the stringency of the national mitigation target for limiting global warming to 2 or 1.5 °C. These rules may be based on cumulative emissions, GDP, population, baseline emissions or a combination thereof (Fujimori et al. 2016).

There is significant intra- and inter-regional variation in estimated carbon prices needed to achieve the NDCs unilaterally. Figure 2.1 shows the carbon prices from different models and modelling studies to achieve the NDC targets through a uniform regional carbon price compared to a global carbon price. Results diverge the most for Japan, the USA and the EU, where estimated carbon prices under unilateral action vary between USD 4 to 645/tCO₂-eq, USD 16 to 607/tCO₂-eq and USD 10 to 2745/tCO₂-eq, respectively. With the exception of South Africa, for the rest of the regions, the higher estimates are derived from models that include only energy-related CO₂ emission reductions and exclude lower-cost land-use emission reductions. Yet, it should also be noted, the full set of 49 models, includes 44 models with only energy-related CO₂ emissions and only 5 that include land-use emissions.

Figure 2.1: Cross-model comparison of carbon prices in 2030 to unilaterally achieve the NDCs



Note: Box-Whisker plot shows the median (line), the first and third quartile (box), and whiskers showing the last datapoints within 1.5 times the interquartile range (IQR). Dots indicate outliers. The number x of data points for each region is given as $[x]$. Some models merge the reported regions into larger blocs so that no results can be included. (Aldy et al. 2016a) summarise the results from four models and report the average results between 2025 - 2030. For the US, (Aldy et al. 2016a) report results for 2025 to reach the (I)NDC, equivalent to the target year for the US commitment. (Böhringer et al. 2021a) summarise results from 15 models for two baselines. Included studies: (Akimoto et al. 2017); (Aldy et al. 2016a); (Aldy et al. 2016b); (Böhringer et al. 2021a); (Dai et al. 2017); (Fujimori et al. 2016); (Liu et al. 2019); (Vandyck et al. 2016)

The substantial difference in carbon prices across regions to meet a given target in all reviewed studies highlights the large potential gains from international cooperation in reducing the costs of

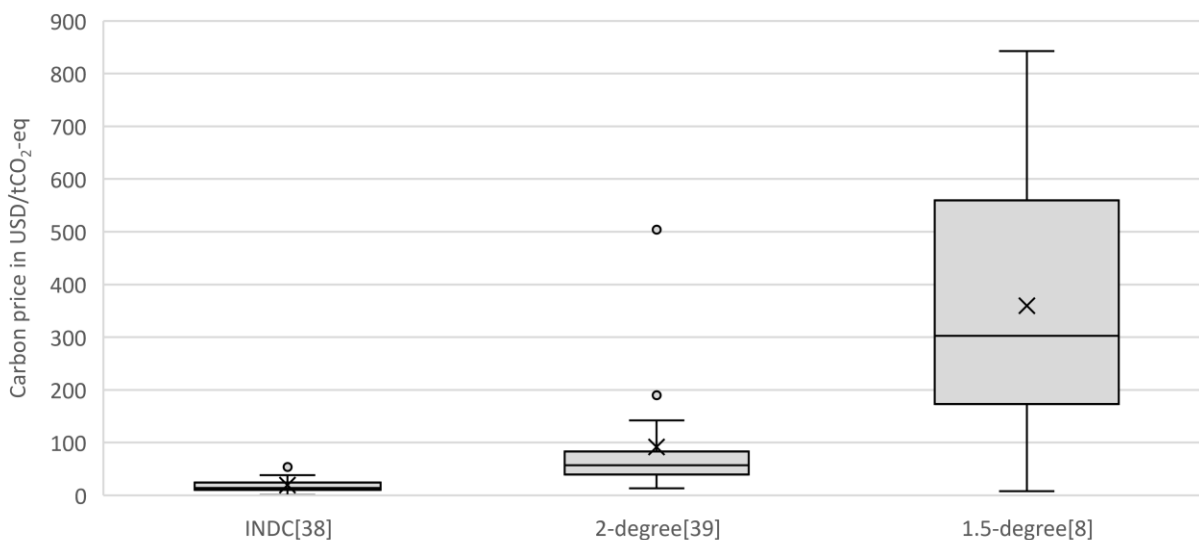
emission reductions. Regional carbon prices tend to be highest in advanced economies (US, EU, Japan, Canada) with average carbon prices around USD 47-119/tCO₂-eq. Note that for all regions this is significantly higher than currently observed carbon prices. Also, the current EU-ETS price of above USD 50/tCO₂-eq is well below the USD 119/tCO₂-eq average price the reviewed studies find for Europe. Altogether, in OECD and G20 countries, less than 10% of GHG emissions were priced above USD 100/tCO₂-eq in 2018 (OECD 2021a).

Given this divergence between actual and modelled carbon prices, the results reported in this section should be interpreted as an upper bound of real-world effects of international cooperation. Simulated prices tend to be lowest in emerging economies (e.g. Russia, India, China and South Africa). In some regions (Russia, India), some model results suggest carbon prices to be zero, implying that those regions would reach their NDC targets under BAU. Low carbon prices could reflect the limited ambition of mitigation targets or a large potential of low-cost abatement options. Other metrics of mitigation costs (e.g. loss of GDP compared to BAU) would result in different regional orderings of costs. If NDCs were achieved jointly (e.g. through a global carbon market), the global carbon price is estimated to be between USD 0.2 and USD 58/tCO₂-eq with an average of USD 18.3/tCO₂-eq. This result of requiring a lower carbon price with joint effort relative to the unilateral effort is in line with the findings for the Kyoto Protocol of 13 models reviewed in (Springer 2003). They showed that the average carbon price for unilateral action in the regulated Annex B countries to meet their Kyoto target was three times higher than with global trading (USD 27/tCO₂-eq vs USD 9/tCO₂-eq respectively).

In the studies that include global cost measures and global cooperation, harmonization of carbon prices would reduce total mitigation costs relative to the unilateral achievement of NDCs. Relative to unilateral carbon pricing, 80% of the models show that harmonized carbon prices result in cost reductions (either in GDP or in terms of welfare) in the order of 48% to 83% (Akimoto et al. 2017; Böhringer et al. 2021a; Fujimori et al. 2016; IETA 2019) and the average is a cost reduction of 64%. This would translate into annual cost savings (see Figure 2.3), estimated variously from zero

to USD 1240 billion in 2030.⁴ 80% of the values are in the range of USD 51 to 365 billion.

Figure 2.2: Cross-model comparison of harmonised global carbon prices for NDCs, 2° and 1.5° targets in 2030



Note: Box-Whisker plot shows the median (line), the first and third quartile (box), and whiskers showing the last datapoints within 1.5 times the interquartile range (IQR). Dots indicate outliers. The number x of data points for each target is given as $[x]$. Included studies: (Akimoto et al. 2017); (Aldy et al. 2016b); (Böhringer et al. 2021a); (Fujimori et al. 2016); (IETA 2019); (Nordhaus 2015); (Qi and Weng 2016); (Vrontisi et al. 2018); (Wei et al. 2018)

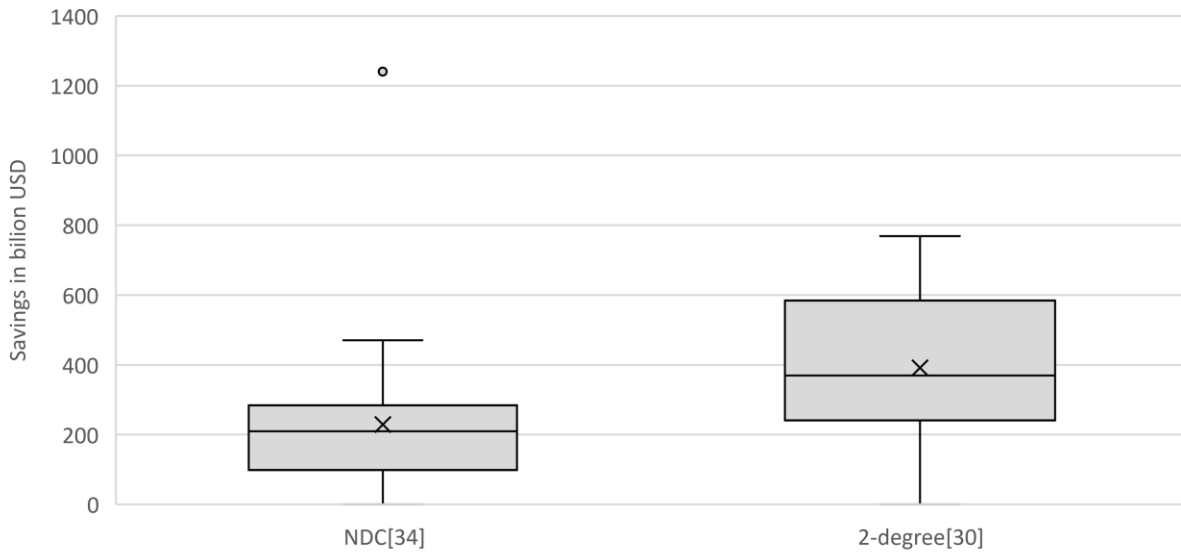
Going beyond achieving current NDCs jointly, coordination on achieving more stringent mitigation targets including those that are compatible with limiting global warming to 1.5 or 2°C relative to pre-industrial levels has a number of implications. First, more ambitious mitigation targets are likely to translate – at least in the shorter term and without accounting for the benefits of climate action - into higher direct regional and global mitigation costs both in terms of necessary global carbon prices to achieve this global target (see Figure 2.2) and of GDP / welfare loss relative to BAU. In the 2°C scenarios, carbon prices increase by on average 4.4 times compared to the NDC scenarios with a range of 2 to 10.8 times. In the 1.5°C scenarios they increase on average by 5 times compared to the 2°C scenarios with a range of 1.6 to 5.3 times. Only Fujimori et al. (2016)

⁴ (Akimoto et al. 2017) do not explicitly report the cost savings from global emissions trading. However, assuming a global GDP of USD 117 trillion in 2030 (EIA 2017), the reported reduction of 0.16% in the co-ordinated case instead of 0.38% in the unilateral achievement of the NDCs would imply cost savings of around USD 259 billion. Note that both (Böhringer et al. 2021a). and (Fujimori et al. 2016) uses loss in terms of welfare measured as Hicksian equivalent variation as cost metric. The values for (Böhringer et al. 2021a) are not included in the paper but were provided by the authors.

report carbon prices for all three climate targets and in the results the price for 1.5°C target is 35 times that for the NDC targets and 10 times that for the 2°C target. Reported changes in GDP/welfare are of the same order. As more stringent targets would translate into higher regional carbon prices that would further diverge, and hence, price harmonization would also increase the absolute gains of international coordination (IETA 2019). The model comparison study of (Böhringer et al. 2021a) finds that through cooperation, the costs (measured as changes in welfare relative to unilateral action) on average reduce by 50% in 2030 for emission reductions in line with the 2°C target and that 80% of the models report cost reductions within the range of 32% to 68% reductions. The full range of costs reductions across all models is 0% to 82%. In absolute terms, this translates into average welfare gains of USD 391 billion in 2030 (see also Figure 2.3). Thus, absolute gains of coordination increase under more ambitious mitigation targets, whereas the relative gains decrease. This is also stressed by one study (IETA 2019) that analyses targets further in the future which are also more ambitious. This study, (IETA 2019) estimates absolute gains of full international coordination would increase from USD 249 billion in 2030 to USD 345 billion in 2050 and USD 988 billion in 2100. Relative gains would decrease from a cost reduction of 63% in 2030 to 41% in 2050 and 30% in 2100.

The identified gains are not shared equally across countries. This is in particular shown by country-level results in (Böhringer et al. 2021a) where at least some of the models show that Africa, Australia/ New Zealand, China, Middle East, Russia, South Korea, USA, Other Americas, and especially, Japan and India have lower welfare costs when NDCs are reached without cooperation and unilateral carbon prices than under a global carbon price. For India, this is even the case for the average across all models. Only Europe, Canada, Brazil and the Rest of Asia unambiguously gain from cooperation in all models. On average, gains are most pronounced in Russia and the Middle East. These findings, are (Böhringer et al. 2021a) driven especially by changes in fossil fuel prices and fossil fuel demand and also (Fujimori et al. 2016) competitiveness effects on world markets. Under global cooperation, abatement shifts to the cheap reduction of coal consumption in China and India implying fewer reductions in oil and gas. This is beneficial for large oil and gas producers (Böhringer et al. 2021a). Producers in countries with projected high unilateral carbon prices such as Canada and Europe that can import allowances under global cooperation significantly benefit from the lower carbon prices brought about by global cooperation on carbon pricing, since this improves their position on world-markets.

Figure 2.3: Cross model comparison of gains from cooperation in billion USD in 2030



Note: Box-Whisker plot shows the median (line), the first and third quartile (box), and whiskers showing the last datapoints within 1.5 times the interquartile range (IQR). Dots indicate outliers. The number x of data points for each target is given as $[x]$. Included studies: (Akimoto et al. 2017); (Böhringer et al. 2021a); (Fujimori et al. 2016); (IETA 2019); (Hof et al. 2017); (Qi and Weng 2016)

Through the same mechanism, producers in allowance-selling countries (e.g. China and India) incur higher costs despite the revenues from selling allowances. Both China and India are characterised by a carbon-intensive economic structure and low abatement costs (and carbon prices) under unilateral NDC achievement. A global carbon market would raise their carbon prices, putting a relatively large burden on their emissions-intensive economy and negatively affecting their international competitiveness vis-à-vis more developed and less emissions-intensive economies (Fujimori et al. 2016). The same is also true for consumers that gain from cooperation if this decreases national carbon prices relative to unilateral action and suffer from global cooperation if it increases national carbon prices relative to unilateral action. In principle, the economic gains from trading for other countries would provide scope to make a global carbon market beneficial for all countries. This could be done in different ways (e.g. via transfers of technology or finance), which are not further assessed here and which could vary widely in terms of political feasibility.

Besides differences in the gains from cooperation across countries, also different household-types are affected differently from carbon pricing and potentially also from cooperation. In general, the

distributional effects of carbon pricing depend on the chosen ways of revenue recycling, the differences in carbon intensities of consumption across different income groups, and varying income sources (labour vs capital income) of different household-types. As laid out in (Böhringer et al. 2021a), carbon pricing without revenue recycling is typically regressive - hurting lower income groups that spend a larger share of their income for energy relatively more than richer households. Revenue recycling e.g. through lump-sum transfers to households can still lead to overall progressive impacts (Böhringer et al. 2021a). Unfortunately, we did not identify studies that analysed the distributive effects of cooperation on within country burden sharing.

2.3.2 Regional harmonisation of carbon prices

Regional harmonisation of carbon prices would reduce mitigation costs of the regional coalition, but to a lower extent than the reduction under full global cooperation. Regional harmonisation could be achieved through linking existing or prospective ETSs which will achieve a uniform price in all regions or through minimum carbon prices as in Canada under the Pan-Canadian Framework on Clean Growth and Climate Change for climate change which will at least reduce the price gap and the resulting inefficiencies. All of the 14 studies we review include the EU. Six of the studies including one multi-model study assess an EU ETS-China linkage, three studies analyse a link between the EU and different coalitions of countries, including G20 countries (e.g. Canada, Japan, Russia, Australia, India, Brazil) and six of the studies cover multi-regional linkages (e.g. Annex I countries⁵). The studies evaluate different reduction targets, extent of sectoral coverage in countries involved and timing and extent (unrestricted versus restricted) of linking, making it difficult to compare these studies. Nevertheless, some common points can be identified.

Studies show that not all countries would gain from linking compared to not linking. The country-specific economic benefits from linking would depend strongly on the country's marginal abatement cost, assumed reduction targets and whether the country is an exporter or importer of emission allowances. In most studies, developed countries are assumed to have the strictest emissions mitigation targets and, thus, the highest carbon prices pre-linking. Linking with jurisdictions with lower carbon prices would reduce the allowance price, leading to benefits in most cases. For instance, in the EU ETS-China studies (Liu and Wei 2016) find that mitigation costs could be reduced by as much as 66% compared to not linking, notably when the price

⁵ Annex I countries include most developed economies. For a list, see: <https://www.oecd.org/env/cc/listofannexicountries.htm>.

difference pre-linking was very high as do most of the other studies. Conversely, allowance-selling countries would not always have economic benefits from linking compared to no-linking as such countries would be negatively affected by rising carbon prices (Hübler et al. 2014; Gavard et al. 2016; Böhringer et al. 2021a) and thus, require compensation. The aggregate gains compared to no-linking would be lower if linking was restricted as in (Li et al. 2019). Region-specific results include:

- Australia is expected to be a buyer of allowances in all analysed scenarios and would gain in terms of welfare in all scenarios (Böhringer et al. 2014a).
- The EU would be buying allowances and gaining in terms of welfare (with the exception of an EU – Australia ETS (Nong and Siriwardana 2018) or an ETS that covers all Annex I regions (Dellink et al. 2014).
- China is found to be a seller of allowances in all studies, but would not benefit from linking in some studies relative to unilateral achievement of mitigation targets in the absence of additional transfers (Gavard et al. 2011; (Böhringer et al. 2021a) or raised climate ambition of linking partners (Liu and Wei 2016).
- In a linked Asian ETS covering China, South Korea and Japan set-up to jointly reach the NDC targets, induces gains mainly for South Korea, while all 15 models of the cross-model comparison only report minor changes in adjustment costs for China and Japan (Böhringer et al. 2021a).
- For Canada, Japan and the US, there is no clear conclusion.

Extending the geographical scope of carbon markets would reduce the aggregate mitigation costs of participating countries but would again not benefit all countries. Adding new coalition members could increase or decrease the allowance price of the extended coalition, depending on the carbon price associated with the new member(s). If the allowance price increased, former allowance importing regions would likely experience a decrease in welfare compared to the status quo in the absence of additional transfer payments as they need to pay higher prices to offset their emission obligations. For example (Gavard et al. 2016) find that if the EU or the US joined a US-China or EU-China coalition, the mitigation costs of the existing coalition members would increase whereas those of the new member would decrease. Conversely, in (Alexeeva and Anger 2016) allowance importing countries tend to gain if the entrance of new countries in the coalition reduces the allowance price. Also (Böhringer et al. 2014a) find that if the allowance price decreases with the

extension of the existing coalition, allowance-selling countries may not benefit relative to no extension.

2.4 Extending coverage of carbon pricing schemes

Energy-related CO₂ emissions from electricity and energy-intensive sectors represent the largest share of emissions covered by existing carbon pricing schemes although some large schemes also include other emissions sources (ICAP 2019). This means that current carbon pricing schemes exclude a number of low-cost abatement opportunities in other sectors (e.g. buildings, agriculture) or from non-CO₂ (NC) GHGs (e.g. methane, nitrous oxide and F-gases), which are not always included in the models reviewed in the previous section. NC-GHGs differ from CO₂ both in terms of radiative efficiency and atmospheric lifespan, making it challenging to calculate a standardised metric. UNFCCC (and the reviewed models) use the Global Warming Potentials (GWP) over 100 years, but this metric does not adequately capture different behaviours of short-lived (e.g. methane) versus long-lived (e.g. CO₂) climate pollutants (Cain et al. 2019).

2.4.1 Extending sectoral coverage of pricing schemes

Expanding sectoral coverage would generally reduce aggregated mitigation costs through harmonising carbon prices across sectors (Böhringer et al. 2009; Böhringer et al. 2014a; Mu et al. 2018) while also reducing the risk of inter-sectoral leakage⁶ (Söder et al. 2019). The benefits from expanding sectoral coverage are higher the greater the risk of inter-sectoral leakage and the higher the difference of marginal abatement costs before the extension.

(Böhringer et al. 2014a) show that step-wise expanding sectoral coverage (e.g. beyond electricity and energy-intensive industry) of hypothetical international carbon markets would reduce mitigation costs for the vast majority of countries. This study also finds that international emissions trading covering only the power sector yields the highest cost savings. They find that a hypothetical link between an EU and US ETS covering only the power sector would reduce aggregate mitigation costs by around 14% by 2020 compared to the unilateral achievement of targets. Expanding the coverage to other sectors (e.g. energy intensive industry, road transport, aviation, all industrial sectors) from the EU-US power market link could further reduce mitigation costs by

⁶ Inter-sectoral leakage refers to a situation, in which a sector-specific climate policy leads to an increase of emissions in a non-regulated sector in the same country.

up to 4 percentage points. This pattern of results also holds true for other combinations of countries, beyond an EU-US link.

The multi-model study by (Böhringer et al. 2021a) also includes a scenario with a global ETS covering all sectors versus a scenario where only the energy intensive and trade exposed (EITE) sectors plus the power sector are covered. Global gains from such a partial ETS relative to no cooperation in the reported NDC scenario are still positive in all models but average gains are reduced by around a third. In a study for China, (Mu et al. 2018) find that real GDP in 2030 is reduced by 2.1% relative to a no policy scenario if China reaches its NDC through an economy-wide ETS. This GDP reduction relative to the no-policy case increases to 10.5% if the ETS only covers eight energy intensive sectors (petrochemicals, chemicals, construction materials, iron and steel, non-ferrous metals, paper, electricity, and air transport) that were responsible for 52% of Chinese CO₂-emissions in 2012. With an ETS that adds nine additional energy intensive sectors so that the ETS covers 76% of 2012 CO₂-emissions, real GDP reduces by only 3.3% relative to a no policy case. Thus, the analysed sectoral expansion reduces costs by almost a third. The reviewed studies on specifically extending the coverage of the existing EU ETS to the transport sector find that this would enhance economic efficiency (Abrell 2010; ECF 2014; Flachslund et al. 2011; Heinrichs et al. 2014). In all these studies, the transport sector would be an allowance buyer. Including transportation into the EU ETS could lower mitigation costs compared to a scenario in which transport is excluded from the EU ETS, but faces additional (e.g. on top of existing gasoline taxes) carbon prices to reduce transport emissions. Yet, the result of (Abrell 2010) is that a reallocation of mitigation obligations from transport to the sectors currently covered by the EU ETS would reduce mitigation costs even more than including transport into the EU ETS.⁷

2.4.2 Extending coverage of pricing schemes to NC-GHG emissions

The abatement potential of NC-GHG emissions is large and predominantly originates from the land-use, land-use change and forestry (LULUCF) sector, but also the energy sector (e.g. methane from natural gas extraction and transmission) (IPCC 2014). Some ETS cover multiple gases, but

⁷ The reason is that constraining transport emissions substantially would reduce tax revenues from pre-existing fuel taxes, leading to a negative welfare effect (Abrell 2010). Yet, this study does not account for other externalities of road transport, including congestion, accidents, and health impacts due to noise, which tends to be larger than the social cost of carbon. Reallocating mitigation obligations from road transport to other sectors would lead to an increase in traffic, exacerbating the negative costs and potentially outweighing the tax interaction effect.

only a few (e.g. New Zealand) are currently planning to price emissions and removals from the LULUCF sector (ICAP 2019).

Extending the coverage of pricing schemes towards NC-GHGs in all economic sectors would reduce mitigation costs as shown in Figure 2.1. A cross-model comparison (Weyant et al. 2006) of 19 global energy models simulate a least-cost policy scenario that is in line with stabilising radiative forcing at 4.5 watts per square meter relative to pre-industrial times by the year 2150⁸. Their results show that in the 21st century, carbon (equivalent) prices in the multi-gas scenario would be, on average, between 23% and 48% lower than carbon prices in the CO₂-only scenario (Weyant et al. 2006). This result holds for all but one model in this study. At the same time, the global GDP losses with multi-gas mitigation are between 0.1% to 4.8%, while those with only CO₂ mitigation range between 0.1% to 6.4%. The maximum difference in cost reduction of 0.3 percentage points by 2025 when including NC-GHGs would amount to annual savings of USD 197 billion, almost equivalent to the reported size of global savings in mitigation costs from unrestricted emission trading to reach the NDCs (see Section 2.3.1).

The general results are confirmed by two other studies. (Ghosh et al. 2012) provide an analysis of CO₂ mitigation policies versus all GHG mitigation policies and generally, extending carbon pricing coverage to include NC-GHGs would also reduce mitigation costs in terms of GDP loss compared to BAU. (Ghosh et al. 2012) also find that a uniform price on global GHG emissions would unambiguously benefit all countries or regions due to the gain in flexibility. The second study is a meta-analysis based on 26 models by (Kuik et al. 2009) and also includes results from (Weyant et al. 2006). They conduct a meta-regression analysis and estimate that the MAC estimates in 2025 are lower by 48% and by 40% in 2050 with multi-gas mitigation rather than CO₂-only mitigation (in line with the results from (Weyant et al. 2006).

2.5 Multilateral fossil fuel subsidy reforms

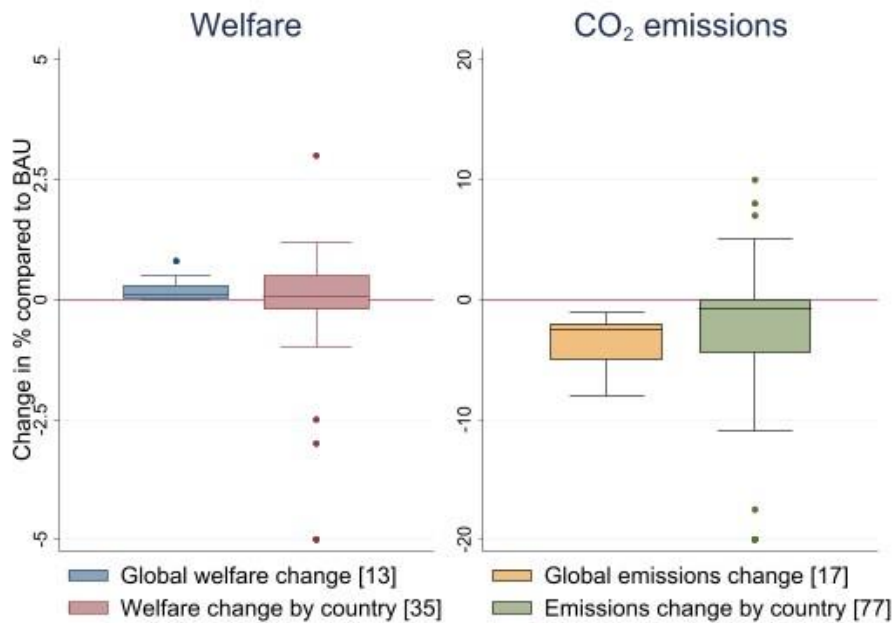
Fossil fuel subsidies (FFS) result in artificially low energy prices, encouraging carbon-intensive modes of consumption and production. In 2009, G-20 leaders called countries to ‘rationalise and phase-out inefficient fossil fuel subsidies that encourage wasteful consumption over the medium term’ (G-20 2009). Decreasing international oil prices, the FFS reform momentum, as well as

⁸ The representative concentration pathway (RCP) 4.5 is not compatible with the Paris Agreement as it is more likely than not to result in global temperature rise between 2 and 3 °C relative to pre-industrial levels(IPCC 2014).

international peer-reviews of national FFS (e.g. Canada, China, Germany, Mexico, US) led to a reduction of FFS between 2013 and 2016 in 76 countries (IEA and OECD 2019). However, estimates also show that in 2017, FFS increased by 5%, reaching USD 340 billion. Despite the pledges of G20-leaders in 2009, FFS in 2020 are still at the same level as in 2010 (OECD 2021b). Consumer FFS account for around 75% of FFS in OECD and partner countries. In (Jewell et al. 2018), a global phase out of FFS by 2030 is estimated to reduce global CO₂ emissions by 1% to 4% relative to BAU. Previous studies indicated that a global phase out of FFS by 2020 could reduce global CO₂ emissions by 5% to 6% by 2035 (Schwanitz et al. 2014) and 6% to 8% by 2050 compared to BAU (Burniaux and Chateau 2014). A more recent analysis by (Chepeliev and van der Mensbrugge 2020) shows that depending on the oil prices, removal of consumption FFS could reduce global emissions by 1.8% to 3.2% in 2030. Figure 2.4 provides a range of global and country-specific emission reductions in response to a global FFS phase-out.

The reviewed studies show that phase out of consumer FFS would reduce emissions in reforming countries, increasing emissions elsewhere, leading to carbon leakage. For example, (Burniaux and Chateau 2014) find that FFS removal in non-OECD countries would reduce global CO₂ (and GHG) emissions by 10% compared to BAU. However, while CO₂ emissions in non-OECD countries would decrease by 16%, emissions in OECD countries would increase by 7% compared to BAU by 2050. All relevant studies find that emission reductions in 2050 with FFS reform tend to be largest in fossil fuel exporting countries, including Russia and Middle Eastern and North African (MENA) countries, amounting to 45% (Burniaux and Chateau 2014), 20% (Schwanitz et al. 2014) and 2% to 10% (Jewell et al. 2018). Lower energy demand in energy exporting countries would translate into reduced global energy prices, which could increase fossil fuel consumption and emissions in energy importing countries (e.g. Europe and Japan). Due to this so-called “energy price channel”, carbon leakage could also arise in case of a global phase out of FFS (Jewell et al. 2018).

Figure 2.4: Effects of multilateral FFSR on welfare and carbon emissions



Box-Whisker plots show the median (line), the first and third quartile (box), and whiskers showing the last datapoints within 1.5 times the interquartile range (IQR). Dots indicate outliers. The number in brackets indicate the number of datapoints. Included studies: (Magné et al. 2014; Burniaux and Chateau 2014; Schwanitz et al. 2014; Jewell et al. 2018; Chepeliev and van der Mensbrugghe 2020)

Sub-global phase out of FFS is less effective than global phase out. If only G20 countries removed FFS by 2020 (“G20 scenario”), then global GHG emissions would reduce by merely 1% by 2050 compared to BAU (Schwanitz et al. 2014). This number would rise to almost 3%, half the reduction of a global phase out, if in addition to the G20 countries all member countries of the Asia-Pacific Economic Cooperation (APEC) removed their FFS (Schwanitz et al. 2014). Carbon leakage, notably to Europe, the US and Japan, would be lower for smaller coalitions of reforming countries. For example, Japan’s GHG emissions would hardly be affected by a phase out of FFS in G20 countries only, but would increase by 3% and 7% for phase outs of G20+APEC and global phase out, respectively (Schwanitz et al. 2014). This pattern is seen because the repercussions of FFS reform on international energy prices are lower for smaller coalitions. While in the G20 scenario, international oil prices would drop by 2% and international gas prices would be hardly affected at all, those prices would decrease by 5% and 10%, respectively, under a global phase out (Schwanitz et al. 2014).

(Böhringer et al. 2021b) show that phasing out producer FFS could lead to negative carbon leakage rates, i.e. decreased emissions in countries not phasing out FFS. Removing producer subsidies (i.e. transfers from taxpayers to producers of fossil fuels) leads to an increase in producer's production costs and, thus, increases both the domestic and international price for fossil fuels, reducing demand emissions both domestically and abroad.

All studies assessed for this paper indicate that joint global welfare would increase with a coordinated FFS reform. Moreover, (Schwanitz et al. 2014) finds that the gains in aggregate welfare would increase with an increasing number of cooperating countries and, thus, in the size of FFS removals. (Burniaux and Chateau 2014) find that removing consumer subsidies in non-OECD countries could lead to a 5% welfare increase (due to lower energy prices) in OECD economies, but only to a 0.2% welfare increase in non-OECD countries. They also find that some countries (e.g. Russia) may not benefit from coordinated FFS removal in the absence of additional transfers. (Chepeliev and van der Mensbrugghe 2020) find that the total removal of all FFS would increase global welfare between 0.02% to 0.1% in 2030 relative to BAU, depending on the oil prices. Similar to (Burniaux and Chateau 2014), Russia also faces welfare losses in (Chepeliev and van der Mensbrugghe 2020). The results on welfare and emissions are summarised in Figure 2.4. Unilateral FFS phase-outs frees up public budget spent on FFS, that could be invested for other purposes or allocated to households, and could trigger a more efficient domestic allocation of resources, both of which would generally enhance domestic welfare. (Burniaux and Chateau 2014) find that under unilateral phase out, energy exporting countries would see the largest welfare gains by 2050 compared to BAU (4%), followed by India (2.3%) and China and Russia (0.4%). In contrast, multilateral phase out of all non-OECD countries would alter the distribution of welfare gains and losses to 2050: Russia would face a welfare loss of 5.8%, oil-exporting countries would show no change in welfare and India and China would gain by 3.0 and 0.7% compared to BAU respectively. The reason is that a multilateral FFS removal would lead to a large decrease in energy demand and global energy prices, reducing the value of fossil fuel exports for energy exporters and offsetting the initial efficiency gains from the reform.

2.6 International sectoral agreements

Sectoral agreements could be one avenue through which (international) carbon prices could be implemented or harmonised for specific economic sectors. Such agreements have the potential to

reduce sector-specific GHG emissions while addressing concerns on competitiveness and carbon leakage in industrialised countries, as well as on economic development in emerging countries (Meunier and Ponsard 2012). Bottom-up sectoral approaches could set binding, but potentially regionally differentiated emission targets for specific sectors, including aviation and energy-intensive trade-exposed (EITE) sectors. Current sectoral approaches include the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA), aiming to stabilise global international aviation emissions at 2019 levels (ICAO 2020), and pledges of the International Maritime Organisation (IMO) to reduce GHG emissions from international shipping by at least 50% by 2050 compared to 2008 “whilst pursuing efforts to phase them out” (IMO 2018).

Results from modelling the impact of sectoral agreements on GHG emissions are limited, but suggest that such agreements could reduce GHG emissions although not cost-effectively. The conclusion is based on only two studies for the cement sector (Voigt et al. 2012) and the energy-intensive sectors (Akimoto et al. 2008).⁹ Sectoral approaches could reduce GHG emissions in industrialised, emerging and developing countries regardless of whether they stipulate absolute (Voigt et al. 2012) or emission intensity (Akimoto et al. 2008) targets in the sectors covered. These agreements would also mitigate competitiveness concerns of sectors and could increase the welfare of participating countries compared to unilateral achievement of sectoral mitigation targets.¹⁰ However, compared to policy scenarios with a uniform global carbon price, sectoral approaches would incur larger welfare losses.

2.7 International coordination on mitigating carbon leakage

Climate policy that is not internationally harmonized faces the risk that economic activities and their associated emissions relocate from countries with higher carbon prices or stricter climate policy to countries with lower prices or less stringent climate policy. This is referred to as carbon

⁹ Other studies are exploring the technical potential and the cost-effectiveness of international co-operation in the low carbon transition of specific sectors, including cement (Cembureau 2013) or iron and steel (WSA 2019). Since they lack international and cross-sectoral repercussions they are not further discussed here.

¹⁰ For example, (Voigt et al. 2012) find that the decrease of EU countries’ output relative to BAU in the cement sector (which is covered by the EU ETS) would be 9% lower when emerging economies (China, Brazil, Mexico) also adopt sector-specific mitigation targets in that sector. Including these countries’ cement sectors in the EU ETS so that all cement facilities face the same carbon price would reduce the loss in EU cement output by even 36%. If the cement sector in all countries faced the same carbon price, this would reduce the welfare loss in the EU and China relative to a climate scenario without sectoral targets while only slightly lessening the welfare of Mexico, leaving Brazil’s welfare unchanged. In contrast, unilateral sectoral targets would lessen the welfare in all emerging economies.

leakage and denotes a situation where the benefits of emissions reduction in a given location are partially offset by emissions increases elsewhere. Coordinated regional implementation of carbon pricing, e.g., through carbon clubs (IISD 2018; Gagnon-Lebrun et al. 2018) or climate coalitions (see section 2.3.2) could reduce carbon leakage within the coalition, but could increase the risk of carbon leakage outside. Furthermore, as economic activity may relocate to countries with lower carbon prices, this would lead to welfare losses in the implementing countries, including loss of jobs and tax revenues, while undermining the environmental effectiveness of carbon pricing.

In the absence of deeper international cooperation, regional or unilateral anti-leakage policies could address carbon leakage but these are always second best to coordinated international climate policies. Anti-leakage policies could increase the environmental effectiveness of international cooperation on carbon pricing by ensuring that emission reductions in a climate-coalition are not offset by emissions increases outside the coalition. As such, anti-leakage policies could, enhance economic outcomes (for coalition members), and/or incentivise more international cooperation.

Most existing carbon pricing schemes address carbon leakage through preferential tax rates, fuel excise taxes or free allocation of emission allowances for ETS, notably for the energy-intensive trade-exposed industry which are most affected by differences in international carbon prices (Ellis et al. 2019). Border carbon adjustments (BCA) was recently also proposed as part of the European Green Deal package. BCA have a number of practical (e.g. measurement of the carbon content), legal (e.g. WTO compatibility) and political challenges (e.g. feasibility, risk of amplifying retaliation measures), which need to be weighed against the potential benefits (Cosbey et al. 2019). Our interest here is in how far they can address the carbon leakage problem.

2.7.1 Effects of anti-leakage policies on GHG emissions

A meta-analysis by (Branger and Quirion 2014) that reviewed 25 modelling studies shows that in the absence of any anti-leakage policy the leakage rates of regional or unilateral climate policy is estimated to range between 5 and 20%.¹¹ This contrasts the empirical ex-post literature, which does not find any evidence of carbon prices on carbon leakage (Dechezleprêtre et al. 2019; Naegele and Zaklan 2019; Venmans et al. 2020). Most of the ex-post studies also do not find negative and statistically significant effects of carbon pricing on firms' competitiveness (Venmans et al. 2020).

¹¹ A leakage rate of 5% implies that a climate policy leading to a reduction of 100 CO₂e emissions within the climate coalition would increase emissions by 5 CO₂e in countries outside.

Part of the reason is that actual carbon prices have been low and safeguards for the industry were in place (e.g. free allowances).

In the modelling literature, the leakage rate depends on a number of factors:

- More stringent mitigation targets would result in higher leakage rates (Böhringer et al. 2012b; Branger and Quirion 2014). The reason is that more stringent mitigation targets would imply higher implicit carbon prices, leaving more scope for carbon leakage. In view of the ambition needed to achieve the goals of the Paris Agreement, this finding highlights the importance of international cooperation to enhance environmental effectiveness and mitigate carbon leakage. Larger coverage of GHGs would decrease carbon leakage (see section 2.4.2) due to increased flexibility of meeting abatement targets.
- Increasing coalition size would reduce the leakage rate (Böhringer et al. 2014a; Böhringer et al. 2012a; Branger and Quirion 2014). (Böhringer et al. 2014a) systematically assess the effects of coalition size on different anti-leakage measures and report that the differences in leakage rates between anti-leakage instruments reduce with increasing coalition size.
- Harmonising the carbon price within the climate coalition would tend to reduce the leakage rate. This is because a harmonised price minimises the trade repercussions in global energy markets. Model assumptions and choices also have a large influence on estimated leakage rates. First, carbon leakage estimates are higher in CGE models than in partial equilibrium models because the former explicitly includes international repercussions affecting the leakage rate. Second, higher trade elasticities (i.e. fewer trade frictions) increase leakage, allowing price shocks to transmit more heavily in international energy markets. This finding is strengthened through (Böhringer et al. 2017) that includes scenarios with different trade elasticities.

Studies that compare different anti-leakage instruments find that all of them would reduce the risk of leakage, but BCA are expected to be the most effective instrument. BCA would lead to the lowest leakage rate compared to free allocation of allowances and industry tax exemptions for different coalitions and different emission reduction targets (Böhringer et al. 2010; Böhringer et al. 2012c; Monjon and Quirion 2011; Böhringer et al. 2012b; Böhringer et al. 2012a). Yet, no anti-leakage policy could entirely mitigate leakage. (Branger and Quirion 2014) in their meta-study find that BCA would reduce the leakage rate on average by six percentage points compared to

scenarios where emission reduction targets are reached without BCA. The reduction in the leakage rate is estimated to be between one and 15 percentage points with some outliers as high as 30 percentage points. More recent studies (Antimiani et al. 2016; Böhringer et al. 2017; Böhringer et al. 2018; Larch and Wanner 2017) also report results within the range of the meta-study and in most studies, none of the anti-leakage policies would be able to completely offset leakage. This is because these policies only target the trade channel but do not explicitly address the energy channel. Hence, (Burniaux et al. 2013) find that BCA would be more effective in reducing leakage for rather small coalitions that have less influence on global fossil fuel prices.¹² (Böhringer et al. 2017) also stress that the negative leakage rate they find for BCA stems from the fact that energy market effects are not considered here.

Most relevant for this paper is the finding that larger coalitions would lead to a lower leakage rate while broadening the regional coverage of GHG emissions, making climate policy more effective. In fact, the size of the coalition of cooperating countries is the single most important factor that determines the extent of carbon leakage (Branger and Quirion 2014). This also highlights the importance of international cooperation as a first-best policy before turning to anti-leakage instruments. As the coalition size increases, the number of regions where emissions could leak to decrease (to zero, in the case of a global coalition with a uniform carbon price). The results from the meta study suggest, on average, a 37% reduction of the leakage rate if instead of only European countries, all Annex I countries except Russia reduced their CO₂ emissions by 15% relative to a benchmark (Branger and Quirion 2014). In some studies, reduction of leakage rates for the same regional extension of the coalition could be as high as 60% (Böhringer et al. 2012a; Ghosh et al. 2012). Adding China to the coalition would reduce the leakage rate by an additional 50% (Ghosh et al. 2012).

2.7.2 Economic and welfare effects of anti-leakage instruments

BCA would be expected to be beneficial for the coalition countries. The results of (Branger and Quirion 2014)'s meta-study suggest that the change in welfare (not accounting for the welfare effect from emission abatement) compared to BAU in the abating coalitions would range from -1.6% to -0.02% without BCA and from only -0.9% to +0.4% with BCA. Hence, BCA would

¹² The results of few studies suggest that implementing BCA would even result in negative leakage rates, meaning that BCA offsets the negative competitiveness effect, and reduces emissions in non-coalition countries (Branger and Quirion 2014).

reduce coalition countries' welfare loss by up to 44%. One of the drivers is that BCA tend to mitigate the reduction in output from climate policy in EITE sectors (Böhringer et al. 2014b). Yet, BCA would usually not be able to restore the welfare levels of BAU scenarios (i.e. without climate policy) since coalition countries still face direct abatement costs.¹³

In many but not all studies BCAs reduce negative welfare effects of unilateral climate policy in the model-regions undertaking this climate policy but mostly they do not establish a cost-neutral situation in the sense that with BCAs, the model regions do not reach the same level of welfare as without any climate policy. BCA would transfer part of the mitigation burden to the non-coalition countries whose exports are taxed (Burniaux et al. 2013; Böhringer et al. 2014b; Dong and Walley 2012; Böhringer et al. 2018; Larch and Wanner 2017). Energy-exporting countries would typically incur the largest welfare loss due to BCA (Weitzel et al. 2012; Böhringer et al. 2018). The welfare losses incurred by non-coalition countries would partly offset the welfare gains of coalition members. Yet, global welfare would decrease as a result of BCA relative to a policy scenario without BCA, also because it causes additional emission reductions (Branger and Quirion 2014).

Allocating free allowances or tax exemptions for industry transfers income from governments to industrial sectors without necessarily changing trade patterns. In contrast to BCA, this would not negatively affect non-coalition countries, but would also not benefit the coalition countries. Yet, the joint welfare loss of both country groups would be higher for allocating free allowances than for BCA (Böhringer et al. 2017).

2.7.3 Strategic incentives to join climate coalitions

As noted above, BCA would usually reduce the welfare of non-coalition members compared to no BCA, providing incentives for countries to avoid the negative welfare effects by joining the climate coalition. Such incentives are mostly analysed using stylized and partly also parameterized game theoretic models¹⁴ and a few CGE models (Böhringer et al. 2016; Weitzel et al. 2012). Overall, they find that BCA could induce participation in climate coalitions but only under very specific assumptions (Al Khourdajie and Finus 2020; Böhringer et al. 2016) or countries. BCA would

¹³ Few studies suggest that the welfare of coalition countries under BCA would be higher than under BAU. This surprising result can derive from trade policy effects, according to which indirect terms-of-trade benefits from taxing exports of foreign countries realised by coalition countries (e.g. OECD) more than offset direct abatement cost for major industrialised regions such as Germany, the United States and Japan (Böhringer et al. 2018).

¹⁴ This literature is summarized by (Al Khourdajie and Finus 2020).

entice more ambitious climate policy outside the coalition only for very low levels of climate ambition (and thus carbon prices) of the coalition (Nordhaus 2015). In fact, BCA would not be able to create a stable global climate coalition even for very low levels of carbon prices. While club participation could be 13 out of 15 model regions for carbon prices below USD 10, participation decreases to 2 regions for carbon prices above USD 10 (Nordhaus 2015). Energy-exporting countries tend to have the largest incentive to join the coalition as they are most adversely affected by BCA (Böhringer et al. 2016; Weitzel et al. 2012) while the studies find incentives only under unrealistic assumption or not at all for other countries and regions. Other hypothetical measures, notably trade tariffs would be more effective than BCA to incentivise non-coalition countries to join the coalition, but would likely breach multilateral trade rules (Nordhaus 2015).¹⁵

2.8 Summary and Conclusions

This paper assesses quantitative estimates of the economic and environmental benefits from different types of international coordination on carbon pricing based on economic modelling studies. Better awareness and understanding of these benefits could encourage governments to increase their ambition on climate action, and thus facilitate countries' efforts to collectively meet the goals of the Paris Agreement. Quantifying the benefits of international coordination on pricing of carbon dioxide (CO₂) emissions and the distribution of these benefits across country groupings could help policy makers to make better-informed decisions about the implications of and potential forms for international coordination. Such forms could include harmonisation of carbon prices (e.g. through global or regional linking of carbon markets), extending coverage of pricing schemes, phasing out fossil fuel subsidies, developing international sectoral agreements and coordination mechanisms to mitigate carbon leakage.

¹⁵ The result of one study suggests that international compensating transfers in form of additional emission allowances are a more efficient instrument to create a stable global coalition than BCA, leading to larger global welfare levels (Weitzel et al. 2012). Trade tariffs could also trigger participation in global climate coalitions when used against non-coalition members because tariffs would increase the cost of non-participation (Lessmann et al. 2009; Nordhaus 2015). Trade tariffs of 1% (Nordhaus 2015) and 1.5% (Lessmann et al. 2009) would be sufficient to form a stable global climate coalition for low levels of climate ambitions (e.g. global carbon price of USD 12.5 per tCO₂e) or low (assumed) trade elasticities. The level of trade tariffs to maintain global co-operation would need to increase for higher trade elasticities (e.g. to 4%, (Lessmann et al. 2009) and higher mitigation ambition (e.g. 3% for USD 25 per tCO₂e, (Nordhaus 2015). However, for higher global carbon prices (USD 50 and USD 100 per tCO₂e), trade tariffs of even 10% would not be sufficient to constitute a stable global climate coalition. Yet, trade tariffs would still trigger participation of some regions (Nordhaus 2015).

Our review shows that all forms of international cooperation on carbon pricing could deliver benefits which include economic benefits (e.g. lower mitigation costs) and environmental benefits (e.g. reducing greenhouse gas (GHG) emissions and carbon leakage). Increasing mitigation in low-cost regions and reducing mitigation in high-cost regions achieves a given aggregate emissions target at a lower cost. Benefits tend to be higher with broader participation of countries, broader coverage of emissions and sectors and more ambitious policy goals (e.g. with emission reduction targets that align with the temperature goals of the Paris Agreement).

Yet, the economic benefits of international cooperation are likely to vary across countries and regions. Most countries would have substantial economic benefits from cooperation because of savings in mitigation cost (for international emissions trading) or reduced energy prices (for multilateral FFS removal). Some forms of cooperation would be unambiguously beneficial for all cooperating countries (e.g. extending the coverage of pricing schemes towards non-CO₂ GHGs, linkages between countries with relatively similar mitigation ambition and abatement costs). Other forms of cooperation (e.g. multilateral FFS removal) would not always generate economic benefits for all countries. Redistributing the economic savings from cooperation across countries (e.g. via carbon market transactions, or potentially direct monetary transfers or technology transfers) could ensure that cooperation provides economic benefits for all countries. However, this may be politically challenging. Reinvesting the economic gains from cooperation into raised climate ambition would reduce long-term climate risks for all countries. Table 2.3 summarizes the core quantitative results and main findings regarding the different forms of cooperation.

Table 2.3: Main quantitative findings for each cooperation instrument

Main results	Specific Evidence
National carbon prices needed to unilaterally reach submitted NDCs vary greatly across countries leaving room for efficiency gains from international coordination on carbon pricing	Average regional simulated carbon prices in 2030 necessary to reach initial NDCs vary between \$6/tCO ₂ in Russia and \$119/tCO ₂ in the EU.
Instead of unilateral carbon pricing, global carbon pricing can significantly reduce the overall costs of reaching NDCs	Global abatement costs for reaching NDCs in 2030 can on average be reduced by 64%. The implied average global costs savings are \$229 billion in 2030.
For stricter targets, cost savings through a globally harmonized price increase in absolute but decrease in relative terms	For the 2°C target, global costs can be reduced by on average by 50% or \$391 in 2030 for a global carbon price compared to regional carbon prices.

Harmonization of carbon prices does not necessarily benefit all regions.	There is no country / region that always gains or loses across all studies from global harmonization of carbon prices. Generally, but especially for regional harmonization, developed regions mostly gain. Especially China, which is the most important exporter for basically all analysed targets and scenarios, does not gain from joining a trading regime in many studies.
Extending the sectoral coverage of pricing schemes reduces aggregate abatement costs	The highest positive effects of sectoral harmonization are found for the electricity sector. Extensions of carbon pricing to smaller sectors like transport or cement have positive, but much smaller effects.
Allowing flexibility in whether to abate CO ₂ or other non-CO ₂ greenhouse gases reduces abatement costs	On average abatement costs would be between 23% and 48% lower in 2030 and 40% lower in 2050 with multi-gas mitigation rather than CO ₂ -only mitigation
Sectoral agreements can reduce negative competitiveness effects of the covered sectors and imply welfare gains for participating countries, yet emission reductions are limited and policy scenarios with a uniform global carbon price are preferable	For the cement sector, one study finds that the decrease of cement production in the EU relative to a no policy case is reduced by around 36% through a joint ETS with the cement sectors of China, Brazil and Mexico.
Globally phasing out fossil fuel subsidies (FFS) reduces GHG emissions and increases global welfare	Globally phasing out FFS reduces global CO ₂ -emissions by 1%-4% by 2030 relative to a no policy case and by 6%-8% by 2050. Emission reductions are largest in fossil fuel exporting countries. Global welfare increases slightly
Anti-leakage instruments are only an imperfect substitute for cooperation on carbon pricing	Border carbon adjustment reduces leakage on average by 6 percentage points compared to scenarios where emission targets are reached without BCA and can reduce coalition countries' welfare loss by up to 44%.

All studies show substantial variation of carbon prices that would be implied by each region unilaterally meeting its specific mitigation targets, indicating a large potential for cost savings from harmonising carbon prices. Using carbon markets to help countries meet the mitigation goals in their Nationally Determined Contributions (NDCs) with a uniform global carbon price has the potential to reduce global mitigation costs by on average 64%, translating into annual cost savings of on average USD 229 billion by 2030. The absolute, but not relative gains are higher for more ambitious mitigation targets. Regional emissions trading (e.g. through linking carbon markets) also brings benefits, albeit to a lower extent than global cooperation. Though there is no country or region that benefits in all studies from global harmonization of carbon prices, most developed countries/regions (e.g. Japan, EU, USA) would benefit economically and even more so from

regional emissions trading, whereas this might not be the case for emerging economies (notably China). China could see a rise in domestic carbon prices under linked markets, which could negatively affect its international competitiveness *vis-à-vis* more developed and less carbon-intensive economies. Similarly, extending the geographical scope of carbon markets by adding new countries would benefit most, albeit not all countries in the absence of additional transfers.

Extending the coverage of carbon pricing schemes by including more sectors or non-CO₂ GHGs would deliver economic and environmental benefits, enabling countries to tap diverse sources of low-cost abatement options. International cooperation on reducing emissions in the power sector is estimated to have the largest potential for saving mitigation costs. Extending the coverage of (harmonised) carbon pricing beyond the power sector (e.g. to transport or industry) would further reduce aggregate mitigation costs, albeit to a lower extent. Extending the coverage of pricing schemes to non-CO₂ GHGs would lead to average lower carbon prices by 23 - 48% by 2030 compared to scenarios covering only CO₂ emissions. Sectoral agreements could potentially reduce sector-specific GHG emissions and mitigate competitiveness concerns but are overall not efficient, though the evidence is scarce.

Global FFS removal by 2030 is estimated to reduce global CO₂ emissions by 1-4% compared to business as usual (BAU). Phasing out consumer FFS would increase domestic energy prices, reducing energy demand and emissions in the reforming countries, but may cause carbon leakage as a result of lower global energy prices, leading to increasing energy demand and emissions in other countries. Unilateral FFS removal would typically lead to economic gains for the reforming country due to more efficient resource allocation. Multilateral FFS reforms would also benefit most countries, notably energy-importing countries, compared to BAU, but would not be beneficial for some energy-exporting economies due to lower global energy prices. Globally, a multi-lateral FFS removal leads to slight welfare gains.

Coordinated implementation or increase of carbon pricing on a sub-global level (e.g. in form of a climate coalition or carbon club) would reduce carbon leakage within the coalition, but could increase carbon leakage outside. In the absence of multilateral agreements or coordinated efforts to reduce leakage, specific policy instruments (border carbon adjustments (BCA), carbon tax exemptions, allocation of free allowances) could reduce the risk of carbon leakage. Among those, BCA is expected to be most effective and would reduce leakage on average by 6 percentage points

and reduce welfare losses of the coalition by up to 44%. Yet, no instrument would be able to eliminate leakage entirely. BCA would bring economic benefits for coalition countries, but would, in general, disbenefit countries outside the coalition as it would transfer part of the mitigation effort to non-coalition countries whose exports essentially become taxed. Given the distributional implications, BCA could, in theory, provide incentives for non-coalition countries to join a climate coalition, but BCA's potential is expected to be limited.

The review is based on economic modelling studies, which are subject to some caveats. First, the studies and models reviewed here, including integrated assessment models (IAMs) and computable general equilibrium (CGE) models, are stylised models that rely on a number of assumptions such as perfect rationality, information, and foresight of actors (e.g. households, firms) as well as perfect and complete markets. These assumptions are rarely observed in the real world. These assumptions lead to results where harmonized carbon pricing always leads to global economic benefits and thus, more broadly the global cost-reductions of the analysed scenarios should be interpreted as an upper bound of potential real-world effects. In fact, the estimated effects from modelling results far exceed those of empirical ex-post studies (see e.g. Section 7). This can be explained by both the underlying assumptions of modelling studies and/or the discrepancy between actual and modelled policy variables (e.g. the level of carbon prices). Second, the results reported in the literature neither capture all benefits associated with international cooperation nor all of its costs. Some models, notably IAMs assess the benefits associated with reduced long-term climate damages, but may not capture the full range of benefits from cooperation, including a reduced risk (and cost) of extreme events, or broader well-being benefits (reduced air pollution, reduced income inequality). Furthermore, most models quantify the short-term economic benefits, but inadequately evaluate the economic dynamics over the long-term. Regarding costs of cooperation, modelling studies typically do not account for the costs of setting up and maintaining cooperation, for harmonizing policies across nations or for monitoring cross-national carbon pricing schemes. The failure to capture the full costs is most pertinent in the most commonly discussed option for international cooperation i.e., international emission trading systems, which brings economic gains, but also results in on average lower international carbon prices in the absence of these costs. These low carbon price estimates that models report without fully capturing the full costs of establishing and maintain an international emissions trading system should not be misunderstood as if the mitigation costs are low. Such a misinterpretation may deter

economic transformation and investments in innovation that would be needed to enable deep decarbonisation to reach net-zero emissions by mid-century.

Lastly, overall our paper focuses on the quantitative results of the identified studies. Each of the proposed types of coordination could face challenges which could be political (e.g., domestic barriers to carbon pricing and fossil fuel subsidy reforms; international burden sharing rules), practical (e.g., measuring emissions for different sectors) or legal (e.g., compatibility with international trade laws) that may impede implementation of carbon pricing. Also, implementing coordination mechanisms would require high levels of trust between the participating jurisdictions. However, the discussion of these challenges is beyond the scope of this paper.

Given these limitations, the reviewed studies nevertheless provide information about the potential reductions in economic abatement costs and/or additional emission reductions through the analysed cooperation scenarios. Even though our paper shows that the literature provides already many insights about the potential gains from international cooperation on carbon pricing and related climate policies, we also identified some problems, gaps and avenues for future research. First of all, it is often challenging to compare different studies due to different regional aggregations, target years, policy stringency, specific scenarios and reported variables and results. For this reason, multi-model studies within a harmonized setting and with harmonized reporting are especially helpful to identify the range of results. The same is true for quantitative meta-analyses. These studies help at the same time to better understand the drivers of results, which even the multi-model studies mostly only touch upon without really explaining what is driving model results. More meta-analyses on issues where already sufficiently many studies exist (such as e.g. a linking of an EU and Chinese ETS or the gains from moving from unilateral to global carbon pricing under the Paris Agreement) could help to derive robust quantitative results and to understand what factors are driving them. Furthermore, some issues like a sectoral extension of carbon pricing, sectoral agreements as well as fossil fuel subsidy reforms have received relatively little attention compared to the classical comparison of unilateral versus global carbon pricing, even though these topics might be of great political interest and practical relevance. Finally, another avenue for future work is to relax the neoclassical assumptions of models (e.g. perfect market, fully rational actors and more linking of economic models with climate models to include feedback effects).

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2.10 Appendix

Structure, metrics and caveats of economic models

Researchers use economic models, including CGE models and IAMs, to assess the effects of climate policy and international cooperation ex-ante. Economic models are a representation of the global economy, covering (representative) households and firms in different sectors (usually 2 to 15, but also up to 60) and different world regions (usually 5 to 20) that are connected through international markets (trade, capital). The time horizon ranges from 2030 or 2050 (CGEs) to as long as 2100 and beyond (mostly IAMs). Economic models require a number of input parameters and assumptions that determine the outputs as a result of the interplay of different systems.

Studies in this survey make use of multiple metrics on the (economic) effects of climate policies. All metrics are usually reported against a business-as-usual (BAU) scenario. While the climate policy's effect on emissions is straightforward and reported as reduced CO₂ or GHG emissions, different mitigation cost metrics exist (Paltsev & Capros, 2013).

- Carbon price represents the marginal cost of an extra unit of emission reductions. Hence, this metric can be interpreted as mitigation effort, but not necessarily as the total cost of a policy.
- Loss in gross domestic product (GDP) represents the macroeconomic costs.
- Loss in welfare usually measures the amount of additional income needed for consumers to compensate for the consumption losses from a policy.

Two major channels can explain differences in the results from economic models across studies (Springer 2003). First, researchers may use different input parameters for BAU projections, including GDP, population, technological progress, etc. Second, results are usually sensitive to the choice of specific model parameters such as production elasticities. Hence, sound research needs to transparently display the assumptions regarding the input and model parameters while checking the robustness of the results for alternative parameter choices.

3. Understanding the range in MAC estimates for fulfilling the NDC pledges¹⁶

Sneha Thube, Sonja Peterson

Abstract

Computable general equilibrium (CGE) models are widely used to conduct ex-ante policy impact valuations. In addition to policy design and policy stringency, structural features of the CGE models also affect the resulting estimates of policy costs. We use harmonized policy analysis results from 15 CGE models and use meta-regression analysis to identify the structural variables that are significant determinants of the global and regional marginal abatement costs (MAC) for fulfilling the initial Nationally Determined Contributions (NDCs). Our results show that models with dynamic characteristics, higher regional disaggregation and with a representation of different electricity technologies estimate higher MACs. On the contrary, modelling endogenous technological change reduces the MAC estimates. Additionally, as to policy design, a statistically significant reduction in global MAC is observed with a fully linked global carbon market (45% reduction) and with a coalition of China, Japan and South Korea (4% reduction). This meta-analysis provides robust quantitative insights about policy modelling and the drivers behind differences across models.

Keywords: Meta-analysis, Marginal abatement cost, Computable General Equilibrium Models, Nationally Determined Contributions, Paris Agreement, Coalition

¹⁶ This paper is included in the IAEE conference proceedings since it was presented at IAEE Online Conference on Energy, Covid, and Climate Change from June 7-9, 2021 Retrievable under: <http://devel.iaee.org/proceedings/article/17196>

3.1 Introduction

Climate change is one of the main challenges that the world is facing today that is expected to have economic effects (Stern 2008). In 2015, 197 countries signed the Paris Agreement and committed to limiting global temperature increase to a maximum of 2-degrees relative to pre-industrial levels (UNFCCC 2015). As a means to fulfil the temperature goal, countries voluntarily pledged greenhouse gas (GHG) emissions reduction targets known as the Nationally Determined Contributions (NDCs). Computable General Equilibrium (CGE) models provide economy-wide policy assessments by accounting for national and international feedback effects. Thus, CGE models are often used to assess the allocational and distributional effects of climate policies (Weyant and Hill 1999; Böhringer et al. 2021). However, results derived from CGE models are subject to parametric and structural uncertainty.

Parametric uncertainty arises from assumptions about crucial model parameters such as elasticities of substitution, labour productivity, autonomous energy efficiency change, or the cost development of new energy technologies. To address sources of parametric uncertainty in CGE models, researchers often supplement their results with a sensitivity analysis to show how changes in assumptions about the key parameters would impact results. Structural uncertainty arises from different structural features of models like static versus dynamic approach, differences in regional and sectoral aggregation, trade specification, and various assumptions on closure rules. In addition to parametric and structural uncertainty across models, the mechanism through which the policy is enforced also contributes to the differences in cost estimates across models.

In addition to the general issue of parametric and structural uncertainty that is applicable to all CGE models, specifically in the context of climate policy analysis, three other factors could explain the variances in mitigation costs (Fischer and Morgenstern 2006). First, the projections of the emissions in the reference scenario since emission reduction targets are usually defined relative to the absolute value of emissions in the reference. Second, the design of the climate policy regimes, particularly the degree of flexibility in meeting the mitigation targets. And lastly, how and where the co-benefits of emission reductions are accounted for.

We identified five studies that review why models differ in their cost estimates for similar climate policy targets. In the context of the Kyoto targets, Springer (2003) presents a literature survey from 25 models related to the price of greenhouse gas (GHG) necessary to reach these targets and

qualitatively explains why there are wide range of estimates. He discusses two primary sources for cost-divergence – the growth rate of emissions in the baseline and model characteristics. In Springer (2003), the discussion of model characteristics is limited to differences in modelling approaches based on top-down versus bottom-up models, technological change representation, and GHG coverage. The other four studies (Fischer and Morgenstern 2006; Hawellek et al. 2003; Kuik et al. 2009; Repetto and Austin 1997) use meta-analysis to quantitatively examine the differences in emission reduction costs across models with a broader set of model characteristics. The first of these studies, Repetto and Austin (1997) focusses on pre-Kyoto literature while the rest are post-Kyoto studies. Each of these studies uses meta-analysis to provide quantitative evidence about which factors are statistically significant in determining the cost estimates generated by numerical simulation models. An overview of the main results from these papers is shown in Table 3.5A in Appendix 3.6.

Concerning the NDC pledges, the Energy Modelling Forum (EMF)¹⁷ organized a cross-model comparison study in 2019. The EMF-36 multi-model comparison on the theme ‘Climate Policies after Paris’ was jointly organized by the Kiel Institute for the World Economy and the University of Oldenburg (Böhringer et al. 2021). The participating models followed the same research design i.e. had harmonized baseline pathways and climate policy targets. Despite the extensive harmonization in baselines, policy design and policy stringency the results from the different models still showed large variations in the costs needed to achieve the NDC targets in 2030. The main results of this study are published in Böhringer et al. (2021). We conduct a meta-regression analysis (MRA) using the results from the EMF-36 study to identify the impact of structural and policy variables on MAC estimates.

We contribute to the meta-analysis literature by considering a new set of CGE models, most of which have not been part of previous meta-studies related to (pre-)Kyoto targets¹⁸. This new generation of models is based on the latest databases, apply updated modelling techniques and, consider a diverse portfolio of new energy technologies. Additionally, in the EMF-36 study, policy targets were modelled by varying stringency of targets and cooperation between regional climate

17 The EMF is a well-known forum that organizes cross-model comparison studies on energy and environmental issues to enrich collective understanding of these problems and provide guidance for policy and future research. See <https://emf.stanford.edu/> for more information.

18 The PACE model was considered in the study by Kuik et al. (2009).

regimes. We use the variation in these scenarios to examine the impact of different degrees of international cooperation on regional and global MACs.

The paper proceeds as follows. In Section 3.2 we present our data and approach and, in section 3.3, the results. Section 3.4 concludes.

3.2 Method

3.2.1 Description of the database

We construct the database for our analysis by using the scenario outputs of the 15 multi-regional CGE models that participated in the EMF-36¹⁹ cross-model comparison study (Böhringer et al. 2021). Subsequently, the results from the scenarios were merged with data on the characteristics of corresponding models to generate the full dataset (see Table 3.3A in Appendix 3.6). All of the models use the GTAP-9 database (Aguar et al. 2016) with 2011 as the base year. Furthermore, labour and capital are immobile across regions in the models. Lastly, each of the 15 models represents international trade with Armington characteristics though the point values of Armington elasticities differ.

In the EMF-36 study-design (see Böhringer et al. (2021).), each model was calibrated to two baselines – called IEO and WEO – until 2030. These two baselines were built using GDP and CO₂ emissions forecasts from two different sources - World Energy Outlook 2018 (WEO 2018) and International Energy Outlook 2017 (IEO 2017). Thus, harmonization of the baselines eliminated any cross-model differences in baseline emission pathways which potentially could have been one of the determinants of differences in MACs (Fischer and Morgenstern (2006)).

The ambition level of the climate policy was calculated based on the initial Nationally Determined Contributions (NDC) that were submitted by countries in 2015. Scenarios were designed for three ambition levels for emission reduction – NDC, NDC+, NDC 2-degree. The NDC targets correspond to the unconditional NDCs, NDC+ to the conditional NDC pledges, and NDC 2-degree to the scaled-up NDC+ pledges needed to reach the 2-degree temperature goal (additional details about calculations are provided in the Appendix in Böhringer et al. (2021)). Typically, for a region the NDC 2-degree targets are the strictest targets and the NDC targets the weakest. However, depending on regional pledges, the NDC+ target may either be stricter or the same as the NDC

¹⁹ Project website: <https://emf.stanford.edu/projects/emf-36-carbon-pricing-after-paris-carpri>

target. For the WEO and IEO baseline, NDC+ targets are identical to NDC targets for regions Brazil (BRA), Canada (CAN), India (IND), Japan (JPN) and South Korea (KOR). Table 3.4A provides the targets for all regions in all of the modelled scenarios.

Lastly, in the EMF-36 study, scenarios were also designed based on different degrees of cooperation between regions and sectors for each ambition level. On the one hand, *ref* represents a stylized scenario of no cooperation while, on the other hand, *global* assumes complete cooperation. In terms of the modelling setup, in *ref* each region reaches its reduction target unilaterally through a national carbon price while in *global* there is an emissions trading scheme (ETS) across all regions and sectors. The rest of the three scenarios depict intermediate levels of cooperation. Sectoral cooperation is modelled in *partial* by introducing an ETS in energy-intensive and trade-exposed (EITE)²⁰ sectors and the power sector across all regions. Finally, two sub-global cooperation scenarios are modelled: *eurchn* with an ETS between Europe and China in EITE sectors and the power sector, and *asia* with an ETS between China, Japan, and South Korea in EITE sectors and the power sector. The share of CO₂ emissions covered by emissions trading is 100% in *global*, around 55% in *partial*, 25% in *eurchn*, and 20% in *asia*.

Abatement costs of a region consist of not only costs arising from domestic mitigation efforts but also from the international feedback effects depending on the international policy setting (Peterson and Weitzel 2016). Therefore, we consider the regional MAC results from each model under the five cooperation scenarios and three ambition as independent observations. This assumption is justified on the basis that the MACs in each of these scenarios have been generated in diverse international mitigation settings (i.e. changes in mitigation targets) and policy cooperation settings, and changes in either of the two dimensions provides a distinct policy setting (Klepper and Peterson 2006).

Through the combination of 15 models, two baselines, three ambition levels, and five cooperation scenarios we have a total of 450 data points for our study. Compared to the number of observations used in the previous studies (see Table 3.5A) we consider this a sufficiently large sample for a robust analysis.

²⁰ This definition includes chemical products; basic pharmaceutical products; rubber and plastic products; non-metallic minerals; mining of metal ores; iron and steel; non-ferrous metals; paper, pulp, and print

3.2.2 Meta-regression analysis

We use meta-regression analysis (MRA) method in our study. MRA is a type of meta-analysis typically used to empirically investigate the variation in results from different studies and explain these diverging results (Stanley 2001; Stanley and Jarrell 2005). Qualitative literature reviews hold strong narrative characteristics and do not examine the quantitative results from studies beyond simple descriptive statistics. Meta-analysis provides a method for reviewing empirical literature based on traditional statistical methods and for understanding the large variation in results between studies on a specific topic (Stanley 2001; Stanley and Jarrell 2005).

In our analysis, we include a total of nine independent variables (see Table 3.1) which we categorize into structural and policy variables. We have chosen structural variables based on the previous meta-analysis studies and the quantifiable²¹ structural differences in the 15 CGE models included in our database. Table 3.3A in Appendix 3.6 provides the data on these structural characteristics.

Table 3.1: Independent variables with description

Structural	Description
<i>region</i>	= (log of) total number of regions
<i>unemp</i>	= 1 if unemployment is characterized, 0 otherwise
<i>dynamic</i>	= 1 if model is dynamic, 0 otherwise
<i>endotech</i>	= 1 if model has endogenous technological change, 0 otherwise
<i>eletyp</i>	= 1 if electricity if model differentiated between fossil and renewable (including nuclear) electricity types, 0 otherwise
<i>armel</i>	= 1 if model strictly uses GTAP Armington elasticities, 0 otherwise
Policy	Description
<i>climtarg</i>	Categorical variable for emission reduction targets 0 if NDC, 1 if NDC+, 2 if NDC 2-degree
<i>coop</i>	Categorical variable for cooperation between regions and sectors 0 if <i>ref</i> , 1 if <i>asia</i> , 2 if <i>eurchn</i> , 3 if <i>partial</i> , 4 if <i>global</i>

Regional aggregation has been shown to be a significant factor in the previous studies (Fischer and Morgenstern 2006; Kuik et al. 2009). In the EMF-36 study, modelling teams reported results for

²¹ Quantification of differences across CGE models is not always trivial. For e.g., the choice of nesting of factors (capital-labour-energy) that modelers use for defining production functions varies across models. The choice of nesting would then determine whether models have a capital-labour substitution elasticity or a capital-energy substitution elasticity. However, quantifying these differences through a single value is not possible and therefore, we only include quantifiable differences as structural variables.

14 identical regions. Seven models directly mapped the GTAP 9 base-data to these reporting regions while the remaining teams aggregated the results to these 14 regions in post-simulation data work. Thus, the variable “*region*” varies between 14 and 44, with the average regional disaggregation being 21 and a standard deviation of 10. Similarly, the aggregation of the energy sectors also plays a role in the costs estimates (Fischer and Morgenstern 2006; Kuik et al. 2009).

Differences in the representation of technological change can have implications on cost estimates from models (Fischer and Morgenstern 2006; Kuik et al. 2009; Repetto and Austin 1997) as it defines the technologies available for mitigation and how agents can substitute between them. Broadly speaking, development of technology can be portrayed either endogenously (e.g., R&D investments or learning-by-doing) or exogenously (e.g., autonomous energy efficiency or backstop technologies) in CGE models (Löschel 2002; Gillingham et al. 2008; Baker et al. 2008; Löschel and Schymura 2013). Excluding endogenous technological change representation could lead to overestimation of abatement costs (Löschel 2002). However, even when endogenous technological change is included there are different impacts on MACs depending on how models characterize technological change and the differences in available technology options (Baker et al. 2008). We create a dummy variable “*endotech*” to differentiate between models that allow for endogenous technological change from the rest, to show differences in technology representation across models. In our database, two models include endogenous technological changes.

Another structural variable that affects policy evaluations is the characterization of trade in a CGE model (Fischer and Morgenstern 2006). Differences in trade structures impact the assessment of climate policies by impacting the competitiveness of energy-intensive industries and the burden sharing across countries (Balistreri et al. 2018). Most commonly CGE models use the Armington trade structure and so do all the models in our database. Given this lack of variation in trade structure type across models we are unable to use it as a structural variable in our analysis. We thus use the source of the point estimates of Armington trade elasticities as a variable²². A modeler’s choice of Armington elasticity could determine the qualitative and quantitative impacts of policy shocks (Mc Daniel and Balistreri 2003; Schürenberg-Frosch 2015). To capture this

22 We considered using the (average) point estimates of Armington elasticities as an alternate variable. However, we again ran into the issue of having difficulty in harmoniously quantifying it since models differ in how Armington trade is differentiated i.e. having regionally differentiated point estimates for sectors, only sector-differentiated elasticities in which case number of sectors is relevant, etc. Thus, we chose the source of elasticities as our structural variable.

distinction between models we include a dummy variable “*armel*” that is set to one for models that strictly use the point estimates of Armington trade elasticities from the GTAP 9 database and zero when other sources of Armington elasticity or capped values of GTAP 9 elasticities. Nine models strictly use the GTAP 9 Armington elasticities, while the rest six either cap the values for specific sectors or use alternate sources.

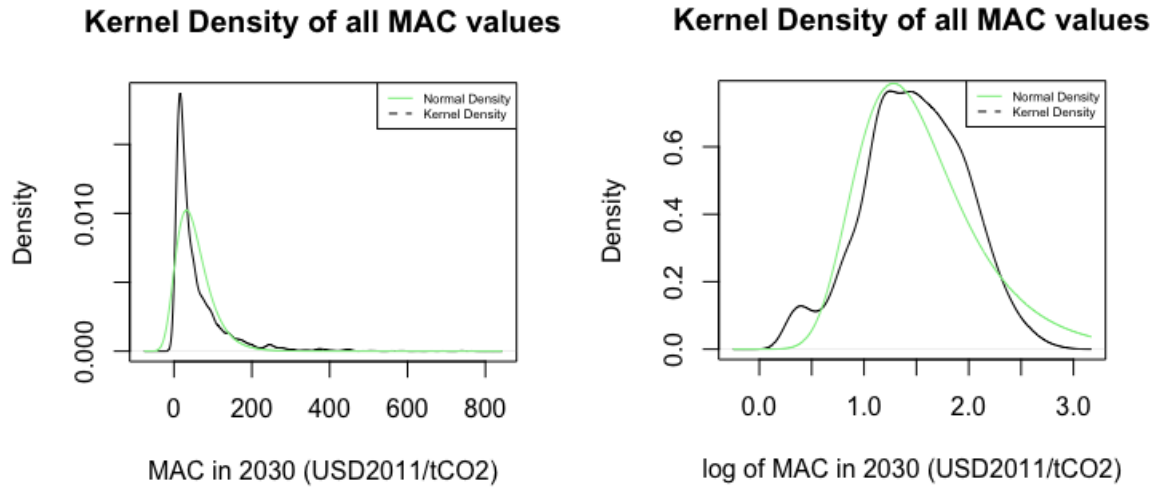
Next, labour market imperfection can be represented differently for e.g., with constrained labour mobility or rigidities in wage adjustments. When using wage curves in a hybrid-CGE model, only minor GDP losses are seen when labour markets are assumed to be highly flexible though accounting for wage rigidities could lead to substantially higher GDP losses (Guivarch et al. 2011). On the contrary, when CGE models portray labour market imperfections via unemployment the CO₂ prices (with lump-sum rebates) for different emission reduction targets are almost identical (Hafstead et al. 2018). Our database consists of one model that considers unemployment while the rest assume a perfect labour market. Therefore, the variable “*unemp*” takes the value one for only a single model.

Generally, the representation of the electricity sector in CGE models can lead to large quantitative and qualitative differences owing to the variation in mitigation potentials and price signals from the electricity sector (Lanz and Rausch 2011). We address this structural feature by defining a dummy variable “*eletyp*” that takes the value one if models differentiate between fossil-based and renewable sources of electricity. We have nine models that differentiate between these two broad electricity technologies. Lastly, the static or recursive-dynamic characteristic of a model also affects the costs resulting from it. In our database nine models are “*dynamic*” while the rest six are static.

Naturally, as highlighted in Section 3.1, features of the policies that are being evaluated also play in role in determining the costs. The policies modelled in our database differ along two dimensions – mitigation targets and the degree of cooperation; thus, we represent both of these dimensions in our explanatory variables. Differences in the stringency of abatement targets have been significant explanatory variables of costs in all previous meta-analysis studies (Fischer and Morgenstern 2006; Kuik et al. 2009; Repetto and Austin 1997). We include a categorical variable “*climtarg*” to represent different abatement targets. The base category of “*climtarg*” is the least ambitious NDC mitigation targets, while “*climtarg*” equals 1 for the NDC+ mitigation targets and equals 2

for the most ambitious NDC 2-degree targets. The categorical variable called “*coop*” captures the level of cooperation between regions and sectors with no cooperation scenario *ref* as the base category.

Figure 3.1: Kernel density of MAC and log MAC in 2030 relative to the normal distribution



The dependent variable in our regression is the logarithmic of the MAC in 2030 as measured in USD 2011. The distribution of MACs for all the observations is slightly right-skewed (see Figure 3.1). Therefore, we use a natural log transformation of the MACs to transform it to a fairly close normal distribution. Equation 1 shows our regression model. Since some models might structurally produce higher MACs than others, we cluster errors at the model level using a robust variance estimator.

Equation 3.1

$$\ln MAC = constant + \beta_1 \ln region + \beta_2 unemp + \beta_3 endotech + \beta_4 eletyp + \beta_5 dynamic + \beta_6 armel + \beta_7 i. climtarg + \beta_8 i. coop + \mu$$

3.3 Results

We begin the analysis of results by first looking at the regression with global MAC in Section 3.3.1 This is followed by an examination of the structural and policy variables on regional MACs in Section 3.3.2.

3.3.1 Global MAC

We start the discussion of the results with the impacts of structural variables on global MACs (column 1 in Table 3.2). The coefficient of “*regions*” is positive and can be interpreted as an elasticity parameter. Therefore, a positive coefficient means that an increase in the number of regions increases the MAC value (this is in line with (Fischer and Morgenstern 2006; Kuik et al. 2009). We can interpret this as a 1% increase in regions leading to less than one percent (0.8%) increase in global MAC. The interpret this result such that a higher number of regions in a model better represent the rigidity of the economic interlinkages between countries thereby, increasing mitigation costs. Thus, a highly aggregated model might underestimate global MACs.

Endogenous technological changes decrease MAC by 55%. This result is in line with the survey by Löschel (2002) though it contradicts Kuik et al. (2009), where induced technical change had a positive coefficient and was weakly significant for determining MAC in the medium-term. Models that strictly use GTAP Armington elasticities have higher MACs. Similarly, recursive-dynamic models also produce higher (by about 28%) MACs than static models. Lastly, a differentiation between fossil and renewable electricity technologies in the model is associated with an increase in MACs by 36%. This can be understood as in models with aggregated electricity sector changes the production cost of electricity from all technologies is the same and thus substitution from one technology to another is costless. However, models that offer even the basic dichotomy in electricity technologies i.e. carbon-intensive and carbon-free technologies, still capture a more realistic depiction of the costs of switching between electricity technologies.

The dummy variable for unemployment has a negative coefficient. Thus, explicitly modelling labour unemployment decreases global MAC by 39%. Only one model in our sample has unemployment explicitly represented in their model, and therefore, we would thus interpret this result with caution.

Among the policy variables, firstly, we see that mitigation targets with higher ambition levels increase MAC. This is a fairly intuitive result and was also seen in earlier studies (Fischer and Morgenstern 2006; Kuik et al. 2009). Since we use a categorical variable “*climtarget*” to represent mitigation target, coefficients for the NDC+ and NDC 2-degree are estimated relative to our base category i.e. the NDC target. Note that the NDC targets are the weakest abatement targets. Global

MACs of mitigating the NDC+ targets are 23% higher while those for NDC 2-degree are 200% higher relative to fulfilling NDC targets²³.

The second policy variable of cooperation level offers insights into which coalitions would lead to statistically significant decreases in global MAC. Again, the coalition variable is modelled categorically thus, all coefficients are relative to our base category i.e. no coalition (scenario *ref* from EM-36). The coefficients of all coalition categories are negative meaning that they have lower global MACs relative to the level of MAC with no coalition. This result is commonly seen in the ex-ante modelling literature where sub-global cooperation decreases the average global MACs (Thube 2021). However, only the coefficient of coalition *asia* and *global* provide a statistically significant reduction in global MAC from cooperation. The decrease in global MAC is highest and equals 45% when full cooperation exists between all the global regions in all sectors. Comparatively, the global MAC is lowered by 4% when there is cooperation between China, Japan, and South Korea in EITE and power sectors.

3.3.2 Regional MAC

The effects of the structural and policy variables on the global MAC are not necessarily mirrored in regional MACs either qualitatively or quantitatively. Thus, we additionally ran region-wise regressions, as shown in Table 3.2. These regressions show the effects of the structural and policy variables on the regional MACs. The errors are again robust and clustered at the model level. Generally, the qualitative effects of model variables on the regional MACs are consistent with that on global MAC regressions, albeit with variation in regional coefficient size. However, with the policy variables the effects are quite diverse across regions. As expected, coefficients of climate target are positive for both NDC 2-degree for all the regions since in this scenario every regional mitigation target becomes stricter relative to NDC. The regional increase in MACs lies between 108% in South Korea to 595% in Africa. We also see a unanimous increase in MACs

²³ The overview paper of the EMF-36 study Böhringer et al. 2021 reports relative changes in MACs using simple averages. The average of global MAC in NDC+ target is (also) 23% higher while that in NDC 2-degree target is 210% higher compared to the NDC target.

Table 3.2: Region-wise regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	GLOBAL	AFR	ANZ	BRA	CAN	CHN	EUR	IND	JPN	KOR	MEA	OAM	OAS	RUS	USA
Model variables															
regions	0.80*** (0.18)	1.20*** (0.37)	0.63*** (0.19)	1.56** (0.68)	1.10*** (0.18)	0.50 (0.36)	0.90*** (0.24)	0.81*** (0.26)	0.75*** (0.20)	0.85*** (0.13)	0.78* (0.37)	1.06*** (0.27)	0.95*** (0.29)	0.78*** (0.25)	0.50** (0.21)
unemp	-0.49*** (0.16)	-0.76*** (0.24)	-0.57** (0.22)	-0.46* (0.25)	-0.47*** (0.12)	-0.54* (0.27)	-0.42** (0.18)	-0.70** (0.24)	-0.55** (0.19)	-0.42*** (0.13)	-0.47** (0.18)	-0.60*** (0.15)	-0.39** (0.17)	-0.73** (0.27)	-0.42** (0.14)
endotech	-0.80*** (0.21)	-0.69** (0.27)	-0.65*** (0.21)	-1.05** (0.39)	-1.01*** (0.33)	-0.59** (0.25)	-1.15*** (0.27)	-0.78*** (0.20)	-0.89*** (0.13)	-1.15*** (0.14)	-0.27 (0.24)	-0.85*** (0.23)	-0.84** (0.29)	-0.29* (0.15)	-0.78*** (0.25)
eletyp	0.31*** (0.10)	0.35 (0.22)	0.23* (0.12)	0.44** (0.15)	0.50*** (0.10)	0.14 (0.15)	0.50*** (0.16)	0.17 (0.13)	0.20 (0.13)	0.17* (0.09)	0.31** (0.11)	0.34*** (0.09)	0.33*** (0.10)	0.14 (0.16)	0.34*** (0.09)
dynamic	0.25** (0.10)	0.36 (0.22)	0.39*** (0.12)	0.28* (0.15)	0.19* (0.10)	0.25 (0.15)	0.38** (0.16)	0.41*** (0.13)	0.56*** (0.13)	0.52*** (0.09)	-0.01 (0.11)	0.24** (0.09)	0.29** (0.10)	0.20 (0.16)	0.25*** (0.09)
armel	1.03*** (0.17)	1.19** (0.41)	0.71*** (0.19)	1.79** (0.68)	1.40*** (0.14)	0.68* (0.34)	1.47*** (0.26)	1.05*** (0.26)	1.24*** (0.19)	1.42*** (0.13)	0.77* (0.37)	1.32*** (0.26)	1.09*** (0.27)	0.96*** (0.25)	0.91*** (0.20)
Policy variables															
1.Climtarg_NDC+	0.21*** (0.01)	0.86*** (0.07)	0.11*** (0.01)	0.06*** (0.00)	0.07*** (0.00)	0.14*** (0.01)	0.08*** (0.00)	0.14*** (0.01)	0.13*** (0.01)	0.07*** (0.00)	0.51*** (0.09)	0.41*** (0.03)	0.57*** (0.03)	0.19*** (0.01)	0.21*** (0.01)
2.Climtarg_NDC 2	1.10*** (0.07)	1.94*** (0.11)	1.30*** (0.08)	0.89*** (0.06)	0.82*** (0.06)	1.20*** (0.08)	0.88*** (0.07)	1.28*** (0.08)	1.44*** (0.09)	0.73*** (0.05)	1.80*** (0.09)	1.48*** (0.09)	1.34*** (0.07)	1.76*** (0.14)	1.05*** (0.07)
1.coop_ASIA	-0.04*** (0.01)	-0.03* (0.02)	-0.01 (0.02)	-0.07 (0.08)	-0.01 (0.01)	0.24*** (0.05)	-0.03 (0.03)	-0.01 (0.04)	-0.44*** (0.08)	-0.99*** (0.17)	-0.16 (0.14)	-0.07 (0.05)	-0.05 (0.04)	-0.03* (0.02)	0.01 (0.01)
2.coop_EURCHN	-0.05 (0.04)	-0.06*** (0.02)	-0.00 (0.02)	-0.07 (0.07)	-0.01*** (0.00)	0.37*** (0.06)	-0.44** (0.17)	0.01 (0.04)	-0.01 (0.02)	-0.03 (0.02)	-0.14* (0.07)	-0.07 (0.04)	-0.05 (0.03)	-0.10*** (0.02)	0.00 (0.01)
3.coop_PARTIAL	-0.14 (0.08)	0.07** (0.03)	-0.05 (0.06)	-0.43*** (0.13)	-0.21** (0.08)	0.60*** (0.08)	-0.40** (0.16)	0.55*** (0.07)	-0.27*** (0.07)	-0.86*** (0.14)	-0.19** (0.08)	-0.16*** (0.04)	-0.49*** (0.08)	0.54*** (0.10)	-0.23** (0.08)
4.coop_GLOBAL	-0.59*** (0.04)	0.22** (0.08)	-0.04 (0.08)	-1.52*** (0.09)	-1.11*** (0.09)	0.98*** (0.08)	-1.79*** (0.06)	0.92*** (0.07)	-0.45*** (0.09)	-2.10*** (0.10)	-0.12 (0.09)	-0.37*** (0.07)	-1.03*** (0.08)	0.92*** (0.11)	-0.75*** (0.05)
Constant	0.17 (0.71)	-2.49 (1.44)	0.23 (0.78)	-1.52 (2.50)	-0.33 (0.67)	-0.24 (1.38)	0.77 (0.97)	-1.43 (1.04)	-0.15 (0.76)	1.42** (0.50)	-0.34 (1.34)	-1.18 (1.00)	-0.09 (1.07)	-1.39 (0.99)	1.27 (0.82)
Observations	450	448	450	446	450	450	450	450	450	450	444	450	450	442	450
R-squared	0.80	0.77	0.73	0.67	0.80	0.69	0.79	0.77	0.73	0.78	0.67	0.80	0.77	0.75	0.78

*Note: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Regions: AFR- Africa, ANZ- Australia and New Zealand, BRA- Brazil, CAN-Canada, CHN-China, EUR-EU27, UK and EFTA members, IND-India, JPN-Japan, KOR-South Korea, MEA-Middle East, OAM-Other Americas, OAS-Other Asia, RUS-Russia, USA-United States*

when regions have to fulfil NDC+ targets rather than NDC targets with the increase being 6% in Brazil to 136% in Africa. Thus, the costs of raising ambition of climate targets come with varying levels of additional costs for the different regions. It is interesting to point out that for five regions - Brazil, Canada, India, Japan and South Korea, though the mitigation target remains the same in NDC and NDC+ (see Table 3.4A) the MACs are nevertheless higher for the NDC+ targets relative to NDC targets. Thus, international policy scenario could impact regional MACs (Klepper and Peterson 2006) even when domestic targets remain identical owing to economic interlinkages between regions.

In the context of climate coalitions, the results provide an interesting illustration of how coalitions differently affect the MACs (relative to no coalition) of the coalition countries versus non-coalition countries. Typically, results show that some countries within the coalition see a decrease in their MAC while others face an increase in regional MACs relative to the no coalition scenario. This is because in the coalition scenarios, countries that participate in a coalition are permitted to trade emission allowances so countries with relatively higher MACs buy relatively cheaper allowances from lower MAC regions and the price at which the allowance is traded determines the equilibrium allowance price of the said coalition. Therefore, from the results shown in Table 3.2 we can interpret that the regions that are part of a coalition and have a negative (positive) coefficient for the coalition variable are buyers (sellers) of permits within that coalition. For e.g., in *asia*, a significant decrease is observed in regional MACs of Japan (-36%) and Korea (-63%), while the regional MAC of China has a significant increase of 27%. Thus, in coalition *asia*, China is the seller of permits while Japan and Korea are the buyers. This is also what is reported in Böhringer et al. (2021). A small but significant decrease in the MAC of 3% is also observed in non-coalition regions of Russia and Africa due to international spill overs. Similarly, in *eurchn* coalition, the Chinese MAC increases by 45% while European MAC decreases by 36%, making China the seller and Europe the buyer of permits. Accompanying significant decreases in MACs are seen in Africa (-6%), Canada (-1%), Middle East (-13%), and Russia (-10%) due to economic interlinkages.

The coefficients of the majority of regions are significant for *partial* and *global* coalition variables. These two coalitions directly affect all the model regions, and thus, we expect to see impacts on all regional MACs. From Table 3.2, we see that with *global* coalition, a significant decrease is seen in regional MACs of Brazil, Canada, Europe, Japan, Korea, Other Americas, Other Asia, and

the USA since these are the regions that typically buyers of permits. The sellers of permits are Africa, China, India, and Russia; therefore, the *global* coalition variable has a positive and significant coefficient for these regions. Australia and New Zealand do not experience a statistically significant impact of any coalition though the regional coefficient always remains negative.

3.4 Discussion and Conclusion

CGE models remain essential tools in conducting ex-ante policy assessments for academics and policymakers. However, since different models produce diverging results for the same policy, policymakers are naturally interested in how robust the policy findings are while understanding the underlying reasons for the divergence in results. We use meta-analysis to shed light on which structural characteristics of a model are important and statistically significant determiners of the cost estimates. Thus, meta-analysis helps to generate coherent conclusions from several quantitative estimates.

Studies that assess policies related to CO₂ emission mitigation often report the marginal abatement costs (MAC) that would be needed to meet the mitigation target. Our meta-analysis shows that when it comes to global MACs, a higher number of regions, energy sectors, differentiation between fossil-based and renewable technologies increase the MAC estimations. Additionally, recursive-dynamic models produce higher MACs than static models and models that use Armington elasticities from GTAP 9 database also yield higher MAC values. Modelling technological progress endogenously and representing unemployment in the model gives lower MAC values.

Policy variables indeed also influence MAC results, as can also be directly seen from the usual scenario analysis. While the EMF36 study by Böhringer et al. (2021) already analyses these effects looking at average affect across the participating models, our meta-analysis is another approach to distil statistically significant effects and to estimate their level. Not surprisingly, the increasing ambition of mitigation targets increases MACs. Generally, cooperation reduces MACs while a fully global coalition (reduction of 45%) or a coalition between Japan, South Korea, and China (reduction of 4%) significantly decreases the global MAC.

In the context of regional MACs, structural variables impact the regional MAC values similar to their impact on global MACs though the effect size and statistical significance varies. Policy

variables, on the other hand, have quite different impacts on regional MACs. Higher emission reduction targets consistently increase the MACs across all regions though in varying magnitudes—firstly, due to differences in the ambition level of the pledges made by regions and secondly due to the economic interlinkages between regions. The effect of the economic interlinkages also becomes evident when different coalitions are established and in addition to coalition regions some non-coalition regions also observe significant changes in their respective regional MACs.

Usually, in a coalition there are significant impacts on the MACs for almost all participating regions. The coalition region that undergoes an increase in MAC is the seller of permits while the region seeing a decrease in MAC is the buyer of permits. In our two coalitions (*global* and *partial*) with participation of all regions, albeit with differences in sectoral participation, most of the participating regions face either a significant increase or decrease in the regional MAC. Australia and New Zealand is the only region that does not see significant reduction by participating in either the *global* or *partial* coalition while the Middle East only sees a significant reduction in *partial* coalition. Unlike *global* and *partial*, in the sub-global coalitions of *asia* and *eurchn* all coalition regions indeed see significant impacts on regional MACs.

From our results we also see that the impact of policy variables on global MACs is quite similar when estimated via meta-regression relative to the percentage changes in average MACs as presented in Böhringer et al. (2021). However, this is not necessarily the case for impacts on regional MACs and we consider this to be a strength of meta-regression analysis in terms of drawing conclusions from cross-model comparisons.

Generally, comparing results from different modelling studies is challenging due to lack of harmonization in the design of study and the model structures. Therefore, meta-analysis can contribute by making comparisons of results from several models. Such an exercise is also valuable for policy decisions since it provides robust evidence about the reasons behind the variance of results from modelling studies as well as their interpretation.

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3.6 Appendix

Table 3.3A: Database of the model characteristics used as independent variables in regression

NAME	DYNAMIC	REGIONS	ELETYP	UNEMP	ARMEL	ENDOTECH
CEPE	0	44	0	0	0	0
C-GEM	1	14	1	0	0	0
CGE-MOD	0	14	1	0	1	0
DART	1	21	1	0	0	0
DREAM	1	14	0	0	1	0
EC-MSMR	1	14	1	0	1	1
EDF-GEPA	0	20	0	1	1	0
ENVISAGE	1	28	1	0	0	0
ICES	1	25	1	0	1	1
JRC-GEM-E3	1	42	1	0	0	0
PACE	0	14	0	0	1	0
SNOW_GL	0	15	0	0	1	0
TEA	1	14	1	0	0	0
UOL	0	15	0	0	1	0
WEGDYN	1	14	1	0	1	0

DYNAMIC = Dynamic, *REGIONS* = # of model regions, *ELETYP* = Fossil and renewable electricity differentiation, *UNEMP* = unemployment, *ENDOTECH* = endogenous technical change, *ARMEL* = GTAP elasticities for Armington

Table 3.4A: Percentage reduction in CO₂ emissions for baseline IEO and WEO and policy targets NDC, NDC+ and NDC 2 degree

	IEO			WEO		
	NDC	NDC+	NDC-2degree	NDC	NDC+	NDC-2degree
AFR	-1.8	-11.0	-20.3	-2.0	-9.6	-25.2
ANZ	-4.7	-4.8	-14.8	-5.9	-5.9	-22.2
BRA	-18.9	-18.9	-27.3	-19.7	-19.7	-33.6
CAN	-21.8	-21.8	-30.0	-19.6	-19.6	-33.5
CHN	-5.0	-5.0	-14.9	-5.0	-5.7	-22.0
EUR	-24.9	-25.0	-32.9	-19.6	-19.7	-33.6
IND	-5.0	-5.0	-14.9	-5.0	-5.0	-21.4
JPN	-8.1	-8.1	-17.7	-1.3	-1.3	-18.3
KOR	-33.4	-33.4	-40.3	-44.5	-44.5	-54.0
MEA	-2.1	-5.6	-15.5	-2.1	-5.5	-21.8
OAM	-6.0	-9.3	-18.8	-5.4	-8.9	-24.6
OAS	-12.2	-21.7	-29.9	-17.3	-26.5	-39.2
RUS	-1.1	-1.3	-11.6	-1.4	-1.7	-18.7
USA	-15.6	-18.2	-26.7	-13.9	-16.6	-31.0
WORLD	-10.2	-12.2	-21.4	-9.6	-11.8	-27.0

Table 3.5A: Overview of meta-analysis literature

Study	# models	# Observations	Measure of cost	Statistically significant variables with positive coefficient (95% CI)	Statistically significant variables with negative coefficient (95% CI)	Variables with no statistical significance
Repetto and Austin (1997)	16	162	% change in GDP relative to baseline for the USA	<ul style="list-style-type: none"> • Constant cost non-carbon backstop technology • Revenue recycling • Averted climate damages are modelled • Averted air pollution damages are modelled • Joint implementation or Global ETS 	<ul style="list-style-type: none"> • % reduction in CO₂ emissions relative to baseline • Squared values of CO₂ emissions reduction • Macro model 	<ul style="list-style-type: none"> • Production substitution possibilities • Number of primary fuel types • Years available for abatement
Fischer and Morgenstern (2006)	11	80	MAC in 2010 (in USD 1990)	<ul style="list-style-type: none"> • Abatement level • # regions • # non-energy sectors • # energy sectors • Noncarbon backstop technology 	<ul style="list-style-type: none"> • ETS in Annex 1 • Infinitely lived households • Armington assumptions on trade • Perfect mobility of capital across regions 	<ul style="list-style-type: none"> • Square of abatement levels • Technological details
Kuik et al. (2009)	26	62 (47 for MAC25 and 49 for MAC50)	MAC in 2025 and 2050 (in USD 2005)	<ul style="list-style-type: none"> • # regions (only MAC50) <p><i>Factors with 90% CI; only MAC25</i></p> <ul style="list-style-type: none"> • Baseline emissions • Induced technical change • Models belonging to and the US Climate Change Science Program 	<ul style="list-style-type: none"> • Climate target in parts per million (ppm) • Multi-gas substitution • Intertemporal optimization by households (only MAC25) <p><i>Factors with 90% CI - MAC25 and MAC50</i></p> <ul style="list-style-type: none"> • # Primary energy sources 	<p><i>For MAC25 only</i></p> <ul style="list-style-type: none"> • # regions <p><i>For MAC50 only</i></p> <ul style="list-style-type: none"> • Baseline emissions • Induced technical change • Top-down model • Models belonging to and the US Climate Change Science Program <p><i>Both MAC25 and MAC50</i></p> <ul style="list-style-type: none"> • Carbon capture and storage • Models belonging to Innovation Modelling Comparison Project

4 A Dynamic Baseline Calibration Procedure for CGE models²⁴

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Abstract:

Baseline calibration of dynamic Computable General Equilibrium (CGE) models is an essential but laborious task. In this paper we suggest a Bayesian approach to flexibly calibrate the baseline of a dynamic CGE model using a large number of input parameters to the forecast trends of multiple output variables. Metamodeling techniques are applied to transform the calibration problem into a tractable optimization problem. This allows the derivation of input parameters needed to match the forecast trends. We demonstrate our method by creating a baseline for the CGE model DART by simultaneously calibrating a mix of macroeconomic, physical and sectoral supply-side output variables until 2030.

Keywords: Dynamic Baseline Calibration, Model Uncertainty, Bayesian approach, Metamodeling, Simulation Optimization, Quantitative Policy Analysis

²⁴ This chapter will be revised and resubmitted to Computational Economics in 2021. An older version of this paper is was published online under the GTAP Conference Proceedings in 2019. Retrievable under:
https://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=5755

4.1 Introduction

Nowadays, Computable General Equilibrium (CGE) models are considered the workhorse models of policy analysis focusing on economy-wide effects induced by exogenous economic shocks or policy interventions (Phimister and Roberts, 2017). For example, CGE models have been widely used to assess the impacts of policies in the area of international trade Hertel, Hummels, Ivanic and Keeney (2007), migration Fan, Fisher-Vanden and Klaiber (2018), agricultural policies (Milczarek-Andrzejewska, Zawalińska and Czarnecki (2018); Taylor, Yunez-Naude and Dyer (1999)), and energy Phimister and Roberts (2017) or climate policies (Webster, Paltsev, Parsons, Reilly and Jacob 2008); Chatzivasileiadis, Estrada, Hofkes and Tol (2019).

However, longstanding criticisms of CGE models include that these models have weak econometric foundations (McKittrick, 1998; Jorgenson, 1984). This criticism arises from the fact that CGE models are rather complex, and available empirical data is relatively limited, implying that it is often impossible to estimate all model parameters econometrically (McKittrick (1998); Jorgenson (1984) or Hansen and Heckman (1996). Thus, the relevant model parameters that determine economic responses of the model to exogenous shocks or policy interventions are either assumed ad hoc or weakly derived from empirical data. Hence, a standard procedure to specify CGE parameters is calibration wherein model parameters are specified based on observed or projected baseline development of central model outputs (Sánchez, 2004).

For a static CGE model, a classical baseline calibration corresponds to calculating endogenous output variables, such that the simulated equilibrium in base-run replicates the economic structure defined by a given empirical social accounting matrix (SAM). A problem of this approach is that, generally, infinite parameter set-ups can exist that are able to exactly replicate a given empirical SAM. Thus, static baseline calibration corresponds to a more or less arbitrary parameter specification. A good case in point is the often-used practice of assuming ad hoc values for relevant elasticities of substitution or transformation, respectively, to determine remaining parameters of corresponding CES- and CET-functions used in CGE models. The selection of elasticity values is not entirely arbitrary but is restricted by a priori expert or theoretical knowledge. Nevertheless, a vast range of parameter set-ups can be generated such that all of them can perfectly replicate a given static baseline.

In response to this criticism Systematic Sensitivity Analysis (SSA) is increasingly used in CGE model applications, i.e., simulating endogenous CGE output variables based on sampled CGE

model parameters that are derived from estimated or assumed distributions (For example, Olekseyuk and Schürenberg-Frosch (2016)). However, while SSA is a good method to reveal induced uncertainty of model outputs explicitly, it is not an appropriate procedure to reduce it. In this context, it is helpful to apply dynamic baseline calibration procedures like using a set of dynamic adaption pathways of relevant output variables to calibrate model parameters. For example, while constructing a dynamic model baseline, CGE modelers use data about the historical developments and forecasts of output variables, like Gross Domestic Product (GDP), sectoral supply curves, Greenhouse Gas (GHG) emissions, to calibrate relevant model parameters. In contrast to static baseline calibration, dynamic baseline calibration has the advantage of directly delivering information on economic responses to exogenous shocks and, hence, is directly informative about model parameters driving these responses.

Technically, dynamic baseline calibration corresponds to a high dimensional optimization problem, meaning that a set of model parameters must be identified so that the base-run equilibrium matches the exogenously defined development paths for a set of output variables. The problem with this method lies in the high dimensionality that arises due to a large number of parameters and output variables. Additionally, a set of theoretical restrictions (like closure rules) on model parameters also need to hold. Moreover, beyond the theoretical parameter restrictions, a priori expert information regarding the empirical range of model parameters generally exists, and prior parameter distributions can formally represent this. Hence, given all these constraints, a Bayesian estimation approach appears to be an appropriate methodological framework for dynamic baseline calibration.

In the literature, some CGE researchers employ a simple “validation” procedure by which they run a model forward over a historical period and compare results for some output variables. This approach can be seen as an informal Bayesian estimation procedure (see for example Gehlhar (1994); Kehoe, Polo and Sancho (1995); Dixon, Rimmer and Parmenter (1997)) and can be helpful to revise parameter estimates and recalibrate the model (Tarp, Arndt, Jensen, Robinson and Heltberg, 2002). However, such approaches are ad hoc and do not yet offer a systematic Bayesian procedure applied as a dynamic baseline calibration.

Alternatively, Arndt, Robinson and Tarp (2002) and more recently Go, Lofgren, Ramos and Robinson (2016) propose a very interesting maximum entropy approach for parameter estimation of CGE models. In detail, their approach applies information theory to estimate CGE parameters based on a sequence of observed SAMs. Their approach can be interpreted as

a special case of the Bayesian approach in Heckeley and Mittelhammer (2008) and hence, already has several advantages as compared to the standard procedure of static calibration methods or ad hoc dynamic baseline calibration methods. However, the approach still has some limitations. First, it is based on particular assumptions regarding a priori parameter distributions, which can be significantly relaxed in a general Bayesian framework (Heckeley and Mittelhammer, 2008). Second, as the authors admit, this approach is focused on an ex-post analysis, and thus it requires empirical observations of corresponding SAMs. Furthermore, this approach cannot be easily extended to baseline calibration of dynamic CGE models based on forecasts of outputs. Moreover, so far, the Cross Entropy (CE)-method has only been applied to single country and static CGE models. At the same time, the authors consider an application of their method to complex dynamic CGE models including multiple sectors and multiple regions as an interesting topic for future research.

In this context, our paper develops a generalized Bayesian approach for baseline calibration of dynamic CGE models. Firstly, it enables the calibration of multiple model outputs of dynamic CGE models based on either historical values or projected trends. Secondly, following Heckeley and Mittelhammer (2008) our proposed Bayesian estimation approach generalizes the CE-method of Arndt et al. (2002); Go et al. (2016) allowing a more direct and straightforward formulation of available prior information, and this can significantly reduce the computational effort involved in finding solutions. Thirdly, applying our approach to calibrate complex multi-region and multi-sector dynamic CGE models still needs high computational effort. Thus, we apply metamodeling techniques (Kleijnen and Sargent, 2000) to replace the CGE model with a simplified surrogate model to reduce complexity and thereby significantly reduce computational effort. Lastly, our Bayesian approach also enables us to simulate endogenous CGE outputs based on sampled model parameters that are derived from the corresponding a posteriori distribution, where technically metamodeling also facilitates Metropolis-Hasting sampling from this a posteriori distribution. We show an application of our method by calibrating a dynamic baseline of the Dynamic Applied Regional Trade (DART-CLIM) model.

The structure of the rest of the paper is organized as follows. Section 4.2 introduces the methodology. Subsequently, in Section 4.3 we apply the method to construct a baseline for the CGE model DART-CLIM. In Section 4.4, we show the calibration results. Moreover, we also conduct a policy assessment by comparing marginal abatement costs derived from the DART-CLIM model when calibrated using our proposed method in comparison with an ad hoc dynamic baseline calibration method. Section 4.5 concludes.

4.2 Methods

Consider a model T which calculates outputs, y , where relations are characterized by a set of model parameters, θ , i.e., it holds:

Equation 4.2

$$T(y, \theta) \equiv 0$$

where T is an I -dimensional vector valued function, y an I -dimensional vector of endogenous output variables and θ a K -dimensional vector of exogenous model parameters.

Determining the values for the model parameters, θ , depends on the type and complexity of the model and data availability. Given enough observed data, y^o , of sufficient quality, θ can be estimated econometrically. In the context of CGE models, data is usually scarce, and therefore, the identification of θ becomes a calibration problem. We want to include prior knowledge like expert knowledge and estimates from other models into the calibration procedure. Therefore, a Bayesian framework for parameter calibration appears a natural choice. Starting with the Bayes Theorem in its proportional form:

Equation 4.3

$$h(\theta|y^o) \propto \mathcal{L}(y^o | \theta) p(\theta)$$

where $p(\theta)$ represents the prior information on model parameters.

The likelihood function, $\mathcal{L}(y^o | \theta)$, represents the information obtained from the data, y^o , together with the assumed model, and $h(\theta|y^o)$ is the posterior density which combines the information from the prior and the data (Zellner, 1971). The posterior density is proportional to the prior density multiplied by the likelihood function. The posterior allows drawing statistical inference about θ using probability statements or deriving point estimates that are optimal with respect to some loss criterion. For example, the value of θ that maximizes $h(\theta|y^o)$ is the mode of the posterior distribution of θ and y^o corresponding to the Highest Posterior Density (HPD)-estimate (Heckelei and Mittelhammer, 2008). In particular, Heckelei and Mittelhammer (2008) show that through appropriate assumptions the Generalized Maximum Entropy (GME) approach suggested by Arndt et al. (2002); Go et al. (2016) can be derived from the general Bayesian framework (Equation 4.3).

Moreover, in the general Bayesian framework, observed variables are noisy, i.e., data $y^o = \{Y_1^o, \dots, Y_N^o\}$ correspond to true variable values, $y = \{Y_1, \dots, Y_n\}$ and noises $\varepsilon = \{\varepsilon_1, \dots, \varepsilon_N\}$. Assume ε_N is *iid* normally distributed, $\varepsilon_n \propto N(0, I)$ implies that the posterior results as:

Equation 4.4

$$h(\theta|y^o) \propto p(\theta) \prod_{n=1}^N p(\varepsilon_n)$$

$$\text{with } (\theta, \varepsilon) \in \Psi := \{(\theta, \varepsilon) | \varepsilon = y^o - y \text{ and } T(\theta, y) \equiv 0\}$$

Building upon this general Bayesian framework, we can develop a dynamic calibration procedure for quasi-dynamic CGE models. Given a forecast for a subset of output variables, $z^o \in y$, of the CGE model, where $z^o = [Z_f^o]$ and $f \in K_F \subset K$ denotes the index of variables for which a forecast is available. Further, let $y_0^o \in y$ denote empirical observations of a subset of CGE-variables in the base run period t_0 , namely let $y_0^o = [Y_{0b}^o]$, with $b \in K_0 \subset K$, denote entries in a SAM in the base run period²⁵. Moreover, we define different subsets of parameters, i.e., $\theta = (\theta_0, \theta_T)$. θ_0 denotes parameter values in the base run period, while θ_T defines parameter changes in a period t compared to the base run. Formally, parameter values in time period t , θ_t , can be subdivided into a base-run parameter, θ_0 and parameter change: $\theta_t = \theta_0 * \theta_T(t)$. Combining this, we can denote a CGE model by the following implicit function:

Equation 4.5

$$F(y_0, z, y \setminus (y_0, z), \theta_0, \theta_T)$$

Additionally, we define $\varepsilon_0 = y_0^o - y_0$ and $\varepsilon_z = z^o - z$, and $\varepsilon = (\varepsilon_0, \varepsilon_z)$. Assuming normal distributions for $\varepsilon \propto N(0, \Sigma_\varepsilon)$ and $\theta \propto N(\bar{\theta}, \Sigma_\theta)$, with the co-variance matrices $\Sigma_\varepsilon, \Sigma_\theta = (\Sigma_0, \Sigma_T)$ diagonal matrices with elements $\sigma_\varepsilon, \sigma_\theta$, we can derive the following optimization problem for the HPD-estimator (see Heckeley and Mittelhammer (2008)):

Equation 4.6

$$\theta^* = \arg \min_{\theta} \underbrace{(\theta_0 - \bar{\theta}_0)' \sum_0 (\theta_0 - \bar{\theta}_0) + (\theta_T - \bar{\theta}_T)' \sum_T (\theta_T - \bar{\theta}_T)}_{\propto p(\theta)} + \underbrace{\varepsilon' \sum_\varepsilon \varepsilon}_{\propto \mathcal{L}(y^o|\theta)}$$

$$\varepsilon_0 = y_0^o - y_0$$

²⁵ It is straightforward to assume that SAM observations are available for more than one period.

$$\varepsilon_z = z^o - z$$

$$0 \equiv F(y_0, z, y \setminus (y_0, z), \theta_0, \theta_T)$$

$$0 \equiv H(\theta_0, \theta_T)$$

$H(\theta_0, \theta_T)$ takes additional parameter constraints into account that are induced by economic theory.

In general, given observations y^o , HPD estimation follows as an optimization problem described by the system Equation 4.6. It is possible to choose other distributions, meaning other extremum metrics, while keeping the general idea the same. However, technically solution of the optimization problem is tedious, primarily since forecasts of the output variables, z^o , are only defined as an implicit function of CGE parameters based on the CGE model (Equation 4.5). Hence, complex methods of simulated optimization have to be applied to solve (Equation 4.65). To reduce complexity and computational effort, we follow physics or mechanical engineering approaches and apply metamodeling techniques. As a result, F is substituted with a metamodel M , which approximates the mapping between model parameters and output variables, y , derived from the original model F . There are various ways of approximating, and in our case, an explicit analytical form (see 2.1 for a short introduction) is appropriate.

Equation 4.7

$$\theta^* = \arg \min_{\theta} (\theta_0 - \bar{\theta}_0)' \sum_0 (\theta_0 - \bar{\theta}_0) + (\theta_T - \bar{\theta}_T)' \sum_T (\theta_T - \bar{\theta}_T) + \varepsilon' \sum_{\varepsilon} \varepsilon$$

$$\varepsilon_0 = y_0^o - y_0$$

$$\varepsilon_z = z^o - z$$

$$0 \equiv M(y_0, z, y \setminus (y_0, z), \theta_0, \theta_T)$$

$$0 \equiv H(\theta_0, \theta_T)$$

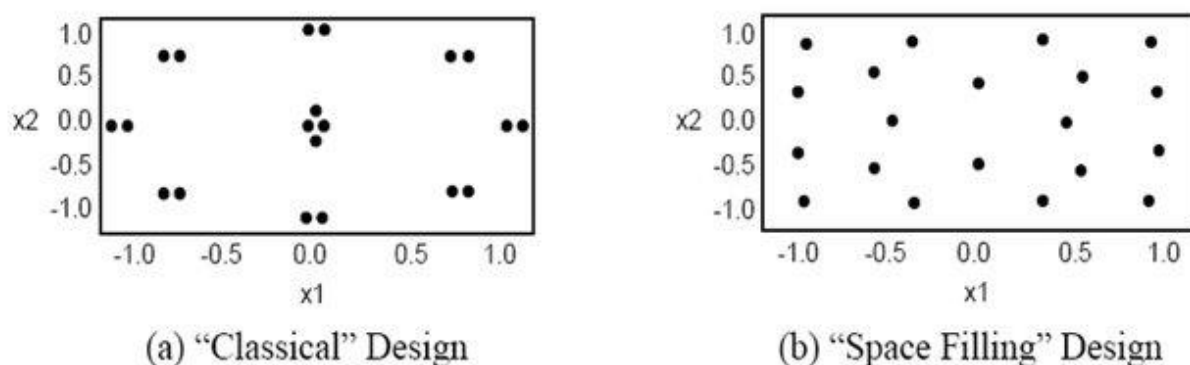
This reformulation allows a straightforward interpretation of the assumed variances σ_{ε} and σ_{θ} . For example, we can interpret σ_{θ} as weights that show how important the matching of the corresponding forecast Z is relative to the other variables. The lower the value of σ_z is, the higher importance it is relative to σ_z' . Another interpretation is how certain we are about a parameter value θ , capturing how much we know, with lower values meaning that we are more certain/knowledgeable about it.

4.2.1 Metamodeling

Metamodeling techniques are widely used in a variety of research fields such as design evaluation and optimization in many engineering applications (Simpson, Peplinski, Koch and Allen, 1997; Barthelemy and Haftka, 1993; Jaroslaw and Raphael T, 1996), as well as in natural science (Razavi, Tolson and Burn, 2012; Gong, Duan, Li, Wang, Di, Dai, Ye and Miao, 2015; Mareš, Janouchová and Kučerová, 2016). In recent years, metamodeling is increasingly being applied to economic research. For example, Ruben and van Ruijven (2001) have applied the approach to bio-economic farm household models to analyze the potential impact of agricultural policies on changes in land use, sustainable resource management, and farmers' welfare; Villa-Vialaneix, Follador, Ratto and Leip (2012) have compared eight metamodels for the simulation of N₂O fluxes and N leaching from corn crops; Yildizoglu, Salle et al. (2012) have applied the technique to two well-known economic models, Nelson and Winter's industrial dynamics model and Cournot oligopoly with learning firms, to conduct sensitivity analysis and optimization respectively. Regardless of the research fields, the metamodeling technique simplifies the underlying simulation model, leading to a more in-depth understanding. The technique also brings the possibility of embedding simulation models into other analysis environments to solve more complex problems, such as the previously described calibration process.

The use of metamodeling entails three steps: selection of metamodel types, Design of Experiments (DOE), and model validation (Kleijnen and Sargent, 2000).

Figure 4.1: Classical and Space-filling Design. (adapted from Simpson et al. (2001))



4.2.1.1. Metamodel Types

Metamodels are classified into parametric and non-parametric models (Rango, Schnorbus, Kwee, Beck, Kinoo, Arthozoul and Zhang, 2013). Parametric models, such as polynomial models (Forrester, Sobester and Keane, 2008; Myers, Montgomery and Anderson-Cook,

2016), have explicit structure and specification. On the other hand, nonparametric models do not depend on assumptions of model specification and determine the InputOutput (I/O) relationship of the underlying simulation model using experimental data. Examples of nonparametric models consist of Kriging models (Cressie, 1993; Yildizoglu et al., 2012; Kleijnen, 2015), support vector regression models (Vapnik, 2013), random forest regression models (Breiman, 2001), artificial neural networks (Smith, 1993), and multivariate adaptive regression splines (Friedman et al., 1991).

In this paper, we focus on the polynomial models that are defined by their order. For example, a second-order polynomial model is given as follows:

Equation 4.8

$$Y = \beta_0 + \sum_{h=1}^k \beta_h \theta_h + \sum_{h=1}^k \sum_{g \geq h}^k \beta_{h,g} \theta_h \theta_g + \eta$$

where $\theta_1, \dots, \theta_k$ are the k independent variables, Y is the dependent variable and η is the error term. The corresponding coefficients β are usually estimated through a linear regression based on least squares estimation (Chen, Tsui, Barton and Meckesheimer, 2006). Some of the advantages of the polynomial models are:

- they have simple forms, which are easy to understand and manipulate
- they require low computational efforts
- they can be easily integrated into other research frameworks

For a more thorough introduction into other types of metamodels, see for example Dey, Mukhopadhyay and Adhikari (2017); Simpson, Lin and Chen (2001).

4.2.2. Design of Experiments

To utilize the metamodels, we need to estimate the corresponding coefficients. We generate the simulation sample by DOE, which is a statistical method of drawing samples in computer experiments (Dey et al., 2017) and perform the estimation by entering the simulation sample into the simulation model. DOE could be set-up in two ways: the classical experimental design and the space-filling experimental design (see Figure 4.1). The former positions multiple sample points at the boundaries and the centre of the parameter space, while the latter evenly

spreads the sample points across the parameter space (Kleijnen, 2015; Dey et al., 2017; Simpson et al., 2001; Sacks, Welch, Mitchell and Wynn, 1989).

4.2.3. Model Validation

Validation refers to assessing whether the prediction performances of the metamodels hold an acceptable level of quality (Kleijnen, 2015; Villa-Vialaneix et al., 2012; Dey et al., 2017). Two samples are needed to assess the quality of a derived metamodel: the training sample and the test sample. The training sample is used to fit the parameters of the metamodel, whereas the test sample is used to validate the trained metamodel. It is important that the test sample includes data points that are not part of the training sample. We want the metamodels to make good predictions not just on the training sample but also for other data points. For this reason, a test sample is essential because it helps us evaluate if the metamodels can be generalized and whether the simulation model can be replaced with them. The following statistics are often considered to assess the validation results.

Equation 4.9

$$R^2 = 1 - \frac{\sum_{i=1}^n (Y_i - Y_i^o)^2}{\sum_{i=1}^n (Y_i - \bar{Y}^o)^2}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - Y_i^o)^2}$$

where Y_i and Y_i^o are the predicted values and true values for the test sample at sample point i , and \bar{Y}^o is the mean of Y^o in the test sample. In regression analysis, R^2 is a statistical measure of how close the data are to the fitted regression line. The root mean squared error (RMSE) is the square root of the variance of the residuals. It indicates the absolute fit of the model to the data – how close the model's predicted values are to the true values.

To compare the prediction performances for dependent variables that have different scales, we introduce the absolute error ratio (AER), which is calculated by taking the absolute value of RMSE divided by the corresponding mean:

Equation 4.10

$$AER = \left| \frac{RMSE}{\bar{Y}^o} \right| = \left| \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - Y_i^o)^2}}{\bar{Y}^o} \right|$$

The metric gives us an idea of how large the prediction errors are in comparison to the true simulated values on average, i.e., the lower the AER values, the better the prediction performances.

4.3 Application

We demonstrate an application of our approach with CGE models by calibrating the DART-CLIM model based on a dynamic baseline. More specifically as shown in Table 4.1, we selected six region-specific output variables resulting in 120 total variables for which exogenous forecasts exist to calibrate nine selected DART-CLIM parameters. All model parameters are either region-specific, sector-specific, or both region-specific and sector-specific, about 1500 in total. Section 4.3.1 introduces DART-CLIM and section 4.3.2 elaborates the approach.

4.3.1 Dynamic Applied Regional Trade Model

DART-CLIM is a recursive multi-region, multi-sector CGE model that is developed at the Kiel Institute for the World Economy and has been used to assess the effects of climate policies on the global economy (Burmeister and Peterson, 2016; Peterson and Klepper, 2007). The model is based on the Global Trade Analysis Project (GTAP)- 9 database (Aguar, Narayanan and McDougall, 2016), which in its fully disaggregated form has 140 regions and 57 sectors. The model version used in this application aggregates the GTAP9 database to 20 regions and 24 sectors. Detailed definitions on regional and sector aggregation are shown in Table 4.4A and Table 4.5A in Appendix 4.7. The model has a medium-term horizon up to 2030.

Studies (Fischer and Morgenstern, 2006; Kuik, Brander and Tol, 2009) have shown that the representation of technical details in CGE models have an impact on policy assessment variables. As the DART-CLIM model is used for ex-ante modelling of climate and energy policies, it is crucial to have a rich depiction of the energy sector. For this purpose, we use the GTAP add-on Power database (Peters, 2016), which provides data on electricity production by different technologies²⁶. Thus, overall DART-CLIM has eight different technologies that produce electricity: solar PV, wind, nuclear, hydroelectricity, coal, gas, oil, and other renewable technologies. Further details on model description can be found in Springer (1998); Klepper, Peterson and Springer (2003); Weitzel (2010).

²⁶ In the GTAP9 - Power database the supply of some of these technologies is differentiated by base-load and peak-load. However, in DART-CLIM we have aggregated the base-load and peak-load sectors to a single homogeneous sector.

Table 4.1: Description of model parameters and output variables used in calibration

Outputs	Description	Data source
gdp	Real regional Gross Domestic Product	OECD (OECD, 2019)
Esolar	Regional electricity production from solar PV	World Energy Outlook (International Energy Agency, 2018): Current Policies Scenario
Ewind	Regional electricity production from wind	
ffu	Total electricity production from fossil sources (coal, oil and natural gas)	
Eother	Rest of electricity technologies excluding nuclear and hydroelectric sources	
emis	Regional CO ₂ emissions from burning fossil fuels	
Inputs	Description	Dimension
tfp	Factor productivity parameter for labour and capital	24 x 20
eei	Autonomous energy efficiency	18 x 20
esub	Elasticity of substitution parameter needed to calculate elasticity of fuel supply	3 x 1
dep	Depreciation rate of capital	20 x 1
eagg_ele	Elasticity of substitution between the eight electricity technologies	20 x 1
preleexp	Exponent for increase of fixed resource for solar PV, wind, and other renewable electricity	3 x 20
esub_res	Elasticity of substitution between fixed resource and capital-labour-energy aggregate	3 x 20
esub_kle	Elasticity of substitution between capital-labour and energy aggregate	24 x 20
armel	Armington elasticity of substitution between imported goods	24 x 1

As mentioned earlier, we want to calibrate the trends of six regional output variables of the DART-CLIM model to their respective forecast trends from external data sources as an application of our proposed calibration method (see Section 4.2). Specifically, we will use the Compound Annual Growth Rate (CAGR) as a measure of the trends for output variables since most of the outputs follow an exponential growth path in the model. Table 4.1 lists the six output variables whose forecasts we aim to meet in the DART-CLIM baseline. The data for the projection of GDP is taken from the OECD macroeconomic forecasts (OECD, 2019) and the data for the electricity production and CO₂ emissions comes from the World Energy Outlook (International Energy Agency, 2018).

Although the DART-CLIM includes eight types of electricity sectors, we use only four of these in our dynamic baseline calibration (see Table 4.1)²⁷. It should be noted that since data on forecasts for each of the fossil-based electricity technologies (coal, oil, and natural gas) are unavailable, we pragmatically decide to match forecasts of the aggregated fossil electricity production.

Table 4.1 shows the model parameters that are used in the calibration process. These parameters correspond to a set of model parameters typically chosen to calibrate CGE models focusing on the analysis of energy and climate policies (Foure, Aguiar, Bibas, Chateau, Fujimori, Lefevre, Leimbach, Rey-Los-Santos and Valin, 2020). Based on the review by Foure et al. (2020), model-specific productivity parameters are calibrated based on matching trends in macroeconomic variables (like gdp). Accordingly, we include the *TFP* and *dep* parameters in our application as they affect the productivity of capital and labour. The model parameter *TFP* is sector-specific. Hence, it directly affects the production trends of individual energy sectors. We further include four additional model parameters (based on the review by Faehn, Bachner, Beach, Chateau, Fujimori, Ghosh, Hamdi-Cherif, Lanzi, Paltsev, Vandyck et al. (2020)), which are typically used by energy modelers to match the energy sector trends specifically. These parameters are autonomous energy efficiency (*eei*), fossil fuel supply elasticity (*esub_res*), elasticity of aggregation between all electricity technologies (*eagg_ele*), and growth parameter for the fixed resource in renewable technologies (*preleexp*). They affect the development of different electricity technologies and impact their production pathways, portfolio of regional electricity technologies, and total CO₂ emissions. Lastly, since results from CGE models are very sensitive to assumed values for trade elasticities as well as for elasticities of substitution (Mc Daniel and Balistreri, 2003; Turner, 2009, 2008), we also include two sets of elasticity parameters, namely, *armel* and *esub_kle*.

4.3.2 Iterative Approach

The main idea is to follow equation 5 estimating the relevant DART-CLIM parameters applying a Bayesian framework. In general, Bayesian estimation could be performed using the original DART-CLIM model. However, since DART-CLIM is a recursive dynamic model, the optimization problem (Equation 4.6) is rather tedious to solve numerically even when powerful

²⁷ Since the development of nuclear and hydroelectric technologies are significantly determined by political will-power or geographical framework conditions, respectively, and less by price effects in electricity markets, we define the production pathways for these two technologies exogenously based on the data from International Energy Agency (2018).

solvers are applied. A solution is to apply simulation optimization (SO) techniques. In particular, we apply a metamodel-based method as a specific class of SO (Kleijnen, 2020). Methods in this class are relatively easy to implement, and they provide a dual benefit of optimization and insight (Barton and Meckesheimer, 2006). Generally, within the class of metamodel-based SO, different approaches can be distinguished by the specific type of metamodel used. This paper focuses on first-order polynomials, which are linear regression models that are applied, for example, in response surface methodology. The advantage of using metamodels is that they may result in more efficient SO methods. Given that our Bayesian estimation includes over 1500 parameters, this implies that the corresponding optimization problem requires a relatively large number of simulations, making it costly. Therefore, the efficiency gained by metamodel-based SO is important²⁸.

First-order polynomial metamodels are efficient and effective, provided they are “adequate” approximations (Kleijnen, 2020). However, polynomial metamodels generally provide only local approximations, so a series of metamodels must be fit as the optimization progresses. Theoretically, certain types of metamodels can also provide a global fit, for example, Kriging models (Kleijnen, 2015). Additionally, different metamodels may be combined into an ensemble (Bartz-Beielstein and Zaefferer, 2017; Friese, Bartz-Beielstein and Emmerich, 2016). Therefore, we have developed an iterative procedure that follows the hill-climbing technique. Algorithm 1 gives an overview of the individual steps.

Algorithm 1 Steps

Start iteration $k \in \{1, 2, \dots\}$

- 1) DOE : θ_k
- 2) Computing simulations
- 3) Estimating and validating metamodels
- 4) Bayesian calibration $\Rightarrow \theta_k^*$
- 5) Evaluating calibration point: $z_k^T = T(\theta_k^*)$
- 6) Exit or start next iteration $k + 1$ at beginning

End

First, we draw a sample of parameters following a specific DOE. In particular, at each step k ,

²⁸ Please note that in the metamodeling literature, metamodels dealing with more than ten parameters are considered as high dimensional (For example, Shan and Wang (2010); Wang, Tang and Li (2011); Sanchez (2006)).

we sample each parameter from an interval $[\theta_k^{lo}, \theta_k^{up}]$. Given that we are looking for local first-order main effects, we generate a metamodel sample Θ^M , where each parameter θ_i is sampled individually within its range, and all other parameters remain unchanged. The sampling strategy is based on the one-factor-at-a-time sampling method (Kleijnen, 2015). For each parameter θ_i the lower bound θ_i^{lo} and upper bound θ_i^{up} are set iteration specific²⁹. In particular, we sample four points for each parameter θ_i – two are close to the current value and other two are further away, as some values might result in infeasible simulations. The sample points Θ_k^M , a $|\theta| * 4x|\theta|$ matrix, are calculated as follows:

$$\vec{\lambda} = [0.05, 0.45, 0.55, 0.95]$$

Equation 4.11

$$\theta_{k,i} = \theta_i^{lo} + \vec{\lambda}(\theta_i^{up} - \theta_i^{lo})$$

$$\Theta_k^M = \begin{bmatrix} \theta_{k,1} & \theta_{k-1,2}^* & \theta_{k-1,3}^* & \dots & \theta_{k-1,|\theta|}^* \\ \theta_{k-1,1}^* & \theta_{k,2} & \theta_{k-1,3}^* & \dots & \theta_{k-1,|\theta|}^* \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \theta_{k-1,1}^* & \theta_{k-1,2}^* & \theta_{k-1,3}^* & \dots & \theta_{k,|\theta|} \end{bmatrix}$$

In addition, a smaller validation sample Θ_k^V (500 parameter specifications) is generated using Latin Hypercube Sample (LHS) (Sacks et al., 1989), where parameters θ_k are sampled simultaneously in the same ranges to test the predictive ability of the estimated metamodels. Computation of the individual runs of the *metamodel*, and *validation samples* is an embarrassingly parallel problem, meaning the computation can easily be split into multiple parallel computations. The parallel computation is time-saving because a single simulation run with DART-CLIM takes about 15 to 60 minutes of computation time, and we need to compute $\approx 4 * 1500 + 500 = 6500$ different runs.

In the second step, we conduct simulation with the DART-CLIM model for each sampled parameter vector. Next, we estimate and validate relevant metamodels M_k (see section 4.2). In particular, we estimate a metamodel $M_{k,j}$ for each output Z_j and perform validation. In the fourth step, we conduct the Bayesian estimation of the model parameter θ_k^* based on the metamodels M_k . Using these metamodels we can solve the slightly adapted problem in equation 11, resulting in θ_k^* :

²⁹ For notational convenience we now denote θ_T with θ , as we keep all other parameters fixed.

Equation 4.12

$$\theta_k^* = \underset{\theta}{\operatorname{argmin}} (\theta - \theta_{k-1})' \sum_{\theta} (\theta - \theta_{k-1}) + \varepsilon_z' \sum_{\varepsilon_z} \varepsilon_z$$

such that,

$$\varepsilon_z = z^o - z$$

$$0 \equiv M_k(z, \theta)$$

$$0 \equiv H(\theta)$$

with $0 \equiv H(\theta)$ denoting theoretical and empirical restrictions on the parameters, as well as the iteration specific bounds $(\theta_1^{lo}, \theta_1^{up})$.

At stage five, we use estimated parameter values to derive trend predictions of relevant output variables, z_k^T , from simulation runs of the original DART-CLIM model. If the prediction error, $\|z^T - z_k^T\|$, is below a critical threshold, then the algorithm stops, and the estimated parameters, θ_k^* , are taken to calibrate DART-CLIM³⁰. Otherwise, the process starts again at step 1, while we sample from the interval $[\theta_{k+1}^{lo}, \theta_k^{up}]$ defined around the estimated parameters θ_k^* .

In this process, we repeatedly search for a local optimum in restricted parameter space. The subsequent parameter space for each parameter is set around its best solution found in the previous iteration for each iteration. This iterative approach builds upon our described methodology (see Section 4.2), though it does not guarantee we find a global optimum as we might get stuck in a local optimum. However, during the process, we can control if the goodness-of-fit (*gof*) of predicting exogenous forecasts improves from iteration to iteration, and we calculate the exact prediction error of our finally selected parameter estimates. It should be further noted that given that the data on forecasts is noisy, it generally makes no sense to achieve parameter estimates that imply perfect predictions. On the contrary, the critical threshold that is set reflects the relative information value of the forecasts vis-a-vis information encapsulated in the prior distribution of the calibrated DART-CLIM parameters.

The process is implemented in a mix of R (R Core Team, 2020), GAMS (GAMS Development Corporation, 2020) and Ansible scripts (Red Hat Software, 2020). The Ansible scripts are used to automate the parallel computation in the cluster environment. The cluster environment uses

³⁰ We set the critical threshold corresponding to an average prediction error of 5%.

the Slurm workload manager (Yoo, Jette and Grondona, 2003). The DART-CLIM model and the Bayesian calibration are implemented in GAMS, while the sampling procedure and analysis are implemented in R (Wickham, Averick, Bryan, Chang, McGowan, François, Golemund, Hayes, Henry, Hester, Kuhn, Pedersen, Miller, Bache, Müller, Ooms, Robinson, Seidel, Spinu, Takahashi, Vaughan, Wilke, Woo and Yutani, 2019; Wickham, 2016; Dupuy, Helbert and Franco, 2015; Dirkse, Ferris and Jain, 2020).

4.4 Results

After five iterations we achieve an average prediction error below 5% of the calibrated baseline in comparison to the forecast trends. In section 4.4.1, we briefly evaluate the validation results by assessing the prediction performances of the metamodels. Subsequently, we assess the calibration results using a *gof* measure and compare the simulated trends with their forecast trends. Finally, we conclude the section with a short demonstration of the importance of baseline calibration on policy implications by simulating the impacts of fulfilling the Paris agreement.

4.4.1 Validation

We use the metamodel sample to derive metamodels which are then used to make predictions of the validation sample. The iterative approach moves the model parameter space recurrently towards a parameter space, where the simulated trends are close to the forecast trends. We check whether the local first-order polynomial metamodels for each iteration can approximate the underlying I/O relationships sufficiently well by assessing the prediction performance by means of the AER (see Equation 4.10):

Equation 4.13

$$AER_{k,j} = \frac{|RMSE_{k,j}|}{|mean_{k,j}|} = \left| \frac{\sqrt{\frac{1}{v} \sum_{u=1}^v (Z_{k,j,u}^F - Z_{k,j,u}^M)^2}}{\frac{1}{v} \sum_{u=1}^v Z_{k,j,u}^F} \right|$$

where $Z_{k,j,u}^F$ and $Z_{k,j,u}^M$ denote the u^{th} simulated and predicted value for the j^{th} output variable in the k^{th} iteration. Moreover, we can see the evolution of the prediction performances across the iterations. The results are shown in Figure 4.2 for each output variable in each region and each iteration, which is denoted by the different colours (see Table 4.6A for detailed results).

The different scales on the y-axes roughly indicate the difficulty of using local first-order polynomial metamodels to approximate the underlying I/O relationships of the DART-CLIM model, particularly in earlier iterations. More specifically, the I/O relationships for gdp, esolar and ewind are relatively easier to approximate than those for ffu, eother and emis as the AER values of the former three outputs are obviously smaller than those of the latter three, particularly in earlier iterations. For example, the AER values for esolar and eother in region EEU in the first iteration (marked by the colour blue in Figure 4.2) are 0.19 and 42.2. One reason is that for ffu, eother and emis, the underlying relationships are more complex than what the metamodels can capture, especially when the model parameter space is large. Moreover, we observe that for each output variable, the AER values tend to decrease across iterations and finally reach relatively low values, indicating fine prediction performances. However, there are cases like eother in region USA, where the AER value is 5.37 after 5 iterations, which indicates a poor prediction accuracy. This means that the underlying relationship is driven by factors like interaction effects, which the first-order polynomial model cannot capture. Nevertheless, we decide to accept these suboptimal metamodels and proceed with the optimization process as there are only a few cases.

4.4.2 Baseline calibration

The paper's primary focus is the derivation of a calibrated dynamic baseline wherein the simulated trends of output variables are close to the forecast trends. We use two measures to assess the calibration results. The first measure is goodness-of-fit (*gof*), which is proportional to the likelihood part ($\mathcal{L}(y^o | \theta)$) of our target function (see Equations 5 and 11). This captures how modelers view the importance of the different targets in the calibration procedure, which is reflected by the relative value of $(\sigma_{z_j}, \sigma_{z_j})$ but also σ_{z_j} to Z_j . A lower value for *gof* means a better fit, with a value of zero indicating a perfect match. The second measure ε follows a more intuitive idea. We compare the simulated values $z_k^F = F(y_0, z, y \setminus (y_0, z), \theta_0, \theta_k^*)$ with the corresponding forecasts z^o and define an indicator function to count the number of output variables that fall in the predefined range:

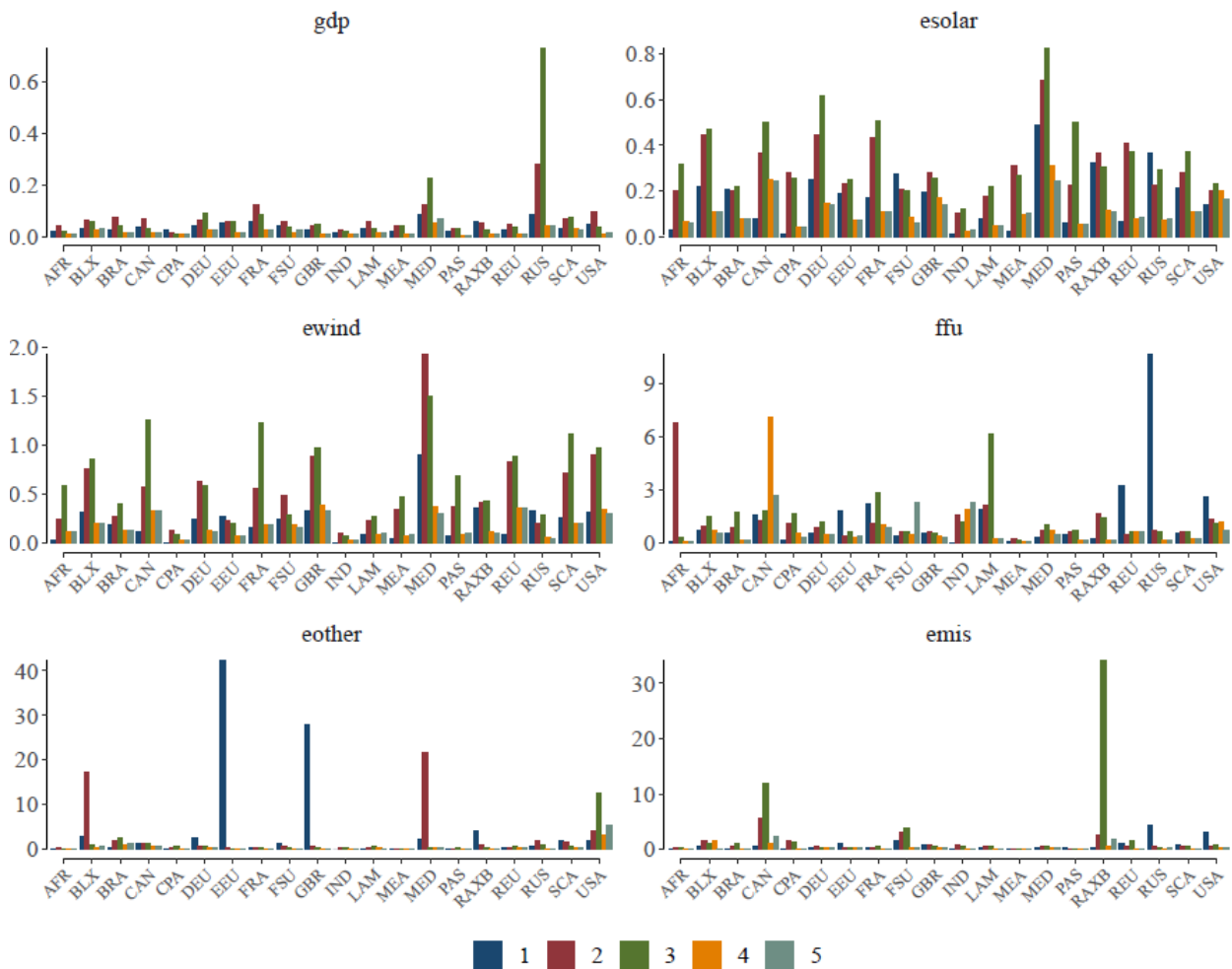
Equation 4.14

$$\varepsilon_{k,j}(Z_j, Z_j^o) = \begin{cases} 1 & \text{if } 0.9 * f(Z_j^o) \leq f(Z_{k,j}^F) \leq 1.1 * f(Z_j^o) \\ 0, & \text{otherwise} \end{cases}$$

with f a simple transformation function. In the simplest case, f is not just the identity function but it can also transform the CAGR back into real values like GDP in US\$.

First, we take a look at the *gof* measure. The results are given in Table 4.2 where “predicted” represent the *gof* computed by using $z_k^M = M_k(z, \theta_k^*)$ while “simulated” represent the *gof* computed by using $z_k^F = F(y_0, z, y \setminus (y_0, z), \theta_0, \theta_k^*)$. The “predicted” *gof* values in the tot column measure the overall deviations z_k^M of from z^0 and thus, reflect the limitations of using local first-order polynomial metamodels to approximate the underlying I/O relationships, particularly in earlier iterations. However, this value decreases with each iteration, meaning that the prediction performance of metamodels is overall getting better. This pattern is also supported by results seen in Section 4.4.1. Moreover, we can discern differences between the *gof* values for “predicted” and “simulated”. The differences are exceedingly large in earlier iterations but subsequently diminish. Thus, the prediction performance of metamodels has a significant influence on the subsequent calibration process, and that the improvement of the prediction performance leads to the refinement of calibration results.

Figure 4.2: The prediction performance (AER) for each output variable in each region and each iteration



Second, in order to have a more straightforward understanding of the calibration results, we take a look at the results of the ε measure in Table 4.2. We transform the CAGR into real values of the year 2030 for each output variable in each region since small differences in CAGRs can lead to large differences in real values after accumulation over the years. Results show that in the last iteration, 108 out of 120 simulated trends fall into the corresponding, $\pm 10\%$ ranges around the forecast trends while in the first iteration, only 67 do, which demonstrates the efficacy of the iterative approach.

These results show that the iterative calibration approach has the power to conduct the baseline calibration of dynamic CGE model DART-CLIM in a structured and systematic way and is capable of producing satisfactory calibration results that can be quantified. Moreover, the approach can be easily applied to different simulation models.

Table 4.2: Goodness-of-fit across iterations (i)

i	Comparison	emis		EOther		ESolar		EWind		ffu		gdp		total	
		gof	ε	gof	ε	gof	ε	gof	ε	gof	ε	gof	ε	gof	ε
1	Predicted	120.61	11	695.54	18	205.43	16	2.36	19	282.42	11	255.99	10	1562.36	85
	Simulated	88.48	14	6632.54	13	1139.42	8	113.93	13	559.22	7	181.37	12	8714.95	67
2	Predicted	82.25	15	1.16	20	1.95	18	1.01	19	136.89	15	95.82	16	319.09	103
	Simulated	81.37	15	1227.83	18	122.05	12	213.74	13	206.53	13	95.81	16	1947.32	87
3	Predicted	84.65	15	13.30	19	0.74	18	0.70	19	141.45	16	79.38	17	320.23	104
	Simulated	91.38	14	170.27	15	562.78	8	203.95	16	220.21	14	68.28	17	1316.88	84
4	Predicted	98.92	15	6.78	19	0.51	18	0.4	19	98.50	15	45.22	18	250.33	104
	Simulated	97.97	15	81.49	19	3.71	20	70.64	19	103.27	15	44.69	18	401.76	106
5	Predicted	84.05	15	1.61	20	0.35	18	0.05	19	75.33	18	20.30	18	181.69	108
	Simulated	77.27	15	111.74	19	9.46	19	1.37	20	85.44	17	21.15	18	306.44	108

4.4.3 Policy implications

The main aim of parameter calibration is to use all available data that is informative regarding the specification of relevant model parameters. Our explanations demonstrate that using existing exogenous forecast data for parameter calibration is a rather complex and laborious process. Thus, one could finally ask is it worth the additional effort. This is an empirical question since parameters resulting from different calibration processes (ad-hoc or not) can imply significantly different economic responses when compared with each other. A central output of DART-CLIM corresponds to marginal abatement costs resulting from simulated climate policies. Hence, we use this variable to assess whether our dynamic calibration method implies significantly different economic responses than a standard calibration procedure. In particular, we impose unilateral emission reduction targets on each region modelled in DART-CLIM. Regional targets correspond to the conditional Nationally Determined Contributions

(NDC)³¹ that countries have pledged under the proceedings of the Paris Agreement as voluntary emission reduction pledges. The emission reduction targets are defined as percentage reductions relative to the baseline. We simulate this policy scenario using three different specifications of DART-CLIM. First, we specify parameters applying our dynamic calibration method, labelled as *base*. Moreover, we use the standard static calibration method based on observed national SAMs in the base year. We refer to this specification method as *uncalibrated*. Finally, we applied our dynamic calibration method again. However, in this case, we only matched three trends, namely regional GDP, total fossil-fuelled electricity, and CO₂ emissions, and stopped the iterations after two rounds. In this case, we matched 48 out of 60 targets in a 10% range and 54 in a $\pm 20\%$ range. This specification is labelled as *counter*.

As can be seen from Table 4.3 estimated carbon prices (marginal abatement costs) differ significantly across parameter specifications. On average, percentage differences in national carbon prices equals $\approx 21\%$ comparing standard parameter calibration with our advanced dynamic calibration method, while on average, this difference amounts to $\approx 16\%$ for the *counter* specification. These results underline that calibration methods matter a lot. In particular, in some regions, for example, PAS or BRA, simulated carbon prices nearly double across applied calibration procedures.

4.5 Conclusion

Nowadays, evidence-based policies correspond to a standard approach of good governance. However, policy analysis is plagued by model uncertainty (Manski, 2018). This holds especially true for CGE-applications as these models usually have weak econometric foundations. Accordingly, given that available data allowing a sophisticated econometric parameter specification remain rather limited, this paper develops an innovative, dynamic calibration method applying a Bayesian estimation framework. The framework is used to build up a dynamic baseline by combining statistical data on macroeconomic variables as summarized in SAMs and forecasts of selected output variables in the presence of a set of theoretical restrictions and a priori expert information regarding the empirical range of model parameters.

In contrast to static baseline calibration, dynamic baseline calibration has the advantage of directly delivering information on economic responses to exogenous shocks and, hence, is

³¹ The method for calculating the emission reduction targets is based on Böhringer et al. (2021).

directly informative about model parameters driving these responses. Technically, the Bayesian framework corresponds to an optimization problem. Given the complexity of most CGE models solution of the latter optimization problem typically corresponds to a challenging problem that cannot be solved with standard numerical solution algorithms. For example, the calibration of the DART-CLIM model includes over 1500 parameters to be specified. In this context, this paper develops a first-order polynomial metamodel-based SO approach. The advantage of using metamodels is that they may result in more efficient SO methods. Given that many simulation runs are required, and each run is quite expensive, this efficiency gain is especially advantageous.

Table 4.3: Policy implications

r	Base	Counter	Uncalibrated (standard calibration)
AFR	10.59	12.65	11.95
BLX	195.14	172.90	158.31
BRA	125.10	82.49	65.11
CAN	38.40	35.56	33.49
CPA	12.10	15.31	14.67
DEU	47.37	51.14	51.40
EEU	27.01	25.20	27.25
FRA	122.71	113.14	103.67
FSU	51.44	51.19	45.00
GBR	41.42	44.73	39.67
IND	16.28	17.43	15.33
LAM	27.72	26.41	22.86
MEA	33.10	30.70	26.76
MED	67.78	85.26	98.18
PAS	53.61	85.46	80.51
RAXB	35.93	41.12	36.42
REU	365.74	272.76	258.10
RUS	11.88	8.44	8.01
SCA	55.32	59.78	47.47
USA	19.99	20.49	28.75

However, a necessary condition that metamodel-based SO deliver good calibration results is that the metamodel delivers a good fit of the original CGE. Since first-order polynomial metamodels are only local approximations of the original CGE, this requires an iterative Markov-chain type mechanism. First-order polynomial metamodels are sequentially estimated and validated until the calibrated model replicates exogenous forecast trends with a sufficiently low prediction error.

To demonstrate the effectiveness of our approach, we apply it to perform the calibration of a dynamic baseline of the DART-CLIM model based on forecasts of six central outputs. Our iterative calibration approach delivers convincing results. For example, for fitting values for about 1500 parameters using a total of 120 outputs (output x region), the prediction errors could be significantly reduced from iteration to iteration until the average prediction error lied below an acceptable range of 5%. Given derived metamodels, matching of parameters is relatively quick and takes less than a minute per iteration. The primary computational effort lies in the computation of required simulations for the metamodels. The simulations can be easily split across multiple computers or be computed in a cluster environment because of their embarrassingly parallel nature.

Furthermore, by comparing ad hoc calibration methods with our advanced approach, we demonstrate that investing additional resources into comprehensive parameter calibration is definitely worth the effort. This is because the central model outputs, i.e., economic response to climate policies encapsulated in regional emission prices reflecting marginal abatement cost differ significantly (in average up to 21% in our application) across model specifications. Finally, our Bayesian approach not only effectively reduces model uncertainty but also enables controlling for it. In particular, it enables the derivation of a posteriori distribution via Metropolis-Hasting sampling not only of all relevant model parameters but also of all relevant endogenous CGE outputs. Please note that technically metamodeling also facilitates Metropolis-Hasting sampling from this a posteriori distribution. Thus, our method is not only an appropriate procedure to reduce model uncertainty but, like SSA, also a good method to explicitly reveal induced uncertainty of model outputs. As Manski (2018) highlighted in his seminal paper, the latter is crucial for conducting consistent model-based policy analysis. In this regard, we consider our Bayesian approach as a promising methodological basis integrating fundamental model uncertainty into evidence-policy analysis. Furthermore, in future work, it should be straightforward to extend the method to calibrate parameters based on multiple time points and not only based on the start and endpoints. Another topic for future research is to extend our calibration method to other complex models like interlinked ecological-economic model frameworks.

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4.7 Appendix

Table 4.4A: List of regions in DART

AFR	Sub Saharan Africa
BLX	Belgium, Netherlands and Luxembourg
BRA	Brazil
CAN	Canada
CPA	China and Hong Kong
DEU	Germany
EEU	Czech Republic, Slovakia, Slovenia, Hungary, Estonia, Latvia, Lithuania, Bulgaria, Romania, Croatia, Austria, Poland
FRA	France
FSU	Kazakhstan, Kyrgyzstan, Ukraine, Albania, Belarus, Armenia, Azerbaijan, Tajikistan, Turkmenistan, Uzbekistan, Georgia, Rest of Europe
GBR	United Kingdom, Ireland
IND	India
LAM	Central- and South America
MEA	Middle East, Northern Africa and Turkey
MED	Mediterranean Europe: Italy, Spain, Portugal, Malta, Greece, Cyprus
PAS	Pacific Asia
RAXB	Australia, New Zealand and Japan
REU	EFTA and rest of the World: Norway, Iceland, Liechtenstein, Switzerland, Overseas Territories and Antarctica
RUS	Russia
SCA	Sweden, Denmark and Finland
USA	USA

Table 4.5A: List of sectors in DART

Non-Energy Products (12)		Energy Products (12)	
CRP	Chemical Products (rubber, plastic)	ENuclear	Nuclear power
ETS	Energy-intensive production	ESolar	Solar power
MOB	Mobility	EWind	Wind power
OLI	Other light industries	EHydro	Hydro power
OHI	Other heavy industries	ECoal	Coal-fired power
SVCS	Services	EGas	Gas-fired power

TND	Transmission and distribution	EOil	Petroleum and coal products for power
ANI	Animal Products	EOther	Biofuels, waste, geothermal and tidal technologies
GRN	Grains	COL	Coal
OSD	Oilseeds	OIL	Petroleum and coal products
CRO	rest of crops	GAS	Gas
RAG	Rest agriculture and other processed food	CRU	Oil

Table 4.6A: AER by target and iteration

target	i	AFR	BLX	BRA	CAN	CPA	DEU	EEU	FRA	FSU	GBR
gdp	1	0.02	0.03	0.02	0.03	0.02	0.04	0.05	0.06	0.04	0.02
	2	0.04	0.06	0.08	0.07	0.01	0.07	0.06	0.13	0.06	0.04
	3	0.02	0.06	0.04	0.03	0.01	0.09	0.06	0.09	0.04	0.05
	4	0.01	0.03	0.01	0.02	0.01	0.02	0.01	0.02	0.01	0.01
	5	0.01	0.03	0.01	0.02	0.01	0.02	0.01	0.03	0.03	0.01
esolar	1	0.03	0.22	0.21	0.08	0.01	0.25	0.19	0.17	0.27	0.19
	2	0.2	0.45	0.2	0.37	0.28	0.44	0.23	0.43	0.21	0.28
	3	0.31	0.47	0.22	0.5	0.26	0.61	0.25	0.5	0.2	0.25
	4	0.06	0.11	0.08	0.25	0.04	0.14	0.07	0.11	0.08	0.17
	5	0.06	0.11	0.08	0.24	0.04	0.14	0.07	0.11	0.06	0.14
ewind	1	0.02	0.31	0.19	0.11	0	0.24	0.27	0.16	0.24	0.33
	2	0.25	0.76	0.27	0.57	0.13	0.63	0.23	0.55	0.48	0.88
	3	0.59	0.85	0.4	1.25	0.09	0.58	0.19	1.22	0.28	0.96
	4	0.11	0.2	0.12	0.33	0.02	0.12	0.07	0.19	0.18	0.38
	5	0.11	0.19	0.13	0.32	0.02	0.11	0.06	0.19	0.15	0.33
ffu	1	0.1	0.72	0.58	1.56	0.12	0.55	1.81	2.18	0.4	0.57
	2	6.78	0.93	0.84	1.24	1.07	0.87	0.4	1.09	0.65	0.62
	3	0.31	1.46	1.76	1.79	1.64	1.21	0.62	2.84	0.66	0.5
	4	0.08	0.73	0.15	7.13	0.54	0.49	0.33	1	0.45	0.36
	5	0.08	0.57	0.16	2.64	0.34	0.44	0.41	0.83	2.29	0.34
eother	1	0.06	2.87	0.34	1.22	0	2.64	42.2	0.33	1.22	27.85
	2	0.21	17.3	1.94	1.24	0.26	0.79	0.29	0.37	0.54	0.5
	3	0.11	1.07	2.61	1.35	0.75	0.66	0.13	0.26	0.29	0.27
	4	0.07	0.4	1.07	0.49	0.05	0.18	0.02	0.08	0.11	0.03
	5	0.08	0.55	1.15	0.51	0.05	0.19	0.02	0.07	0.15	0.03
emis	1	0.04	0.58	0.13	0.42	0.05	0.28	0.9	0.3	1.6	0.81
	2	0.24	1.41	0.47	5.54	1.64	0.55	0.34	0.38	3.02	0.86
	3	0.14	1.07	0.94	11.96	1.2	0.37	0.28	0.47	3.76	0.42
	4	0.04	1.56	0.08	1.03	0.1	0.16	0.27	0.07	0.19	0.22
	5	0.04	0.14	0.08	2.19	0.08	0.15	0.22	0.07	0.23	0.2
target	i	IND	LAM	MEA	MED	PAS	RAXB	REU	RUS	SCA	USA
gdp	1	0.01	0.03	0.02	0.09	0.02	0.06	0.03	0.08	0.03	0.05
	2	0.03	0.06	0.04	0.12	0.03	0.05	0.05	0.28	0.07	0.1

	3	0.02	0.03	0.04	0.22	0.03	0.02	0.04	0.73	0.07	0.04
	4	0.01	0.01	0.01	0.05	0.01	0.01	0.01	0.04	0.03	0.01
	5	0.01	0.01	0.01	0.07	0.01	0.01	0.01	0.04	0.03	0.01
esolar	1	0.01	0.08	0.02	0.49	0.06	0.32	0.06	0.36	0.22	0.14
	2	0.1	0.17	0.31	0.68	0.22	0.36	0.41	0.23	0.28	0.2
	3	0.12	0.22	0.27	0.82	0.5	0.31	0.37	0.29	0.37	0.23
	4	0.02	0.04	0.1	0.31	0.05	0.12	0.08	0.07	0.11	0.2
	5	0.03	0.05	0.1	0.24	0.05	0.11	0.08	0.08	0.11	0.16
ewind	1	0	0.08	0.04	0.9	0.07	0.36	0.08	0.33	0.26	0.31
	2	0.1	0.22	0.35	1.92	0.36	0.41	0.83	0.2	0.71	0.9
	3	0.07	0.27	0.47	1.49	0.68	0.43	0.88	0.29	1.12	0.97
	4	0.03	0.08	0.07	0.36	0.08	0.11	0.35	0.05	0.2	0.34
	5	0.03	0.09	0.08	0.3	0.09	0.1	0.36	0.04	0.2	0.3
ffu	1	0.02	1.85	0.05	0.32	0.5	0.21	3.19	10.64	0.51	2.57
	2	1.58	2.13	0.2	0.69	0.66	1.64	0.45	0.71	0.58	1.35
	3	1.2	6.15	0.15	0.98	0.67	1.41	0.59	0.6	0.6	1.06
	4	1.9	0.24	0.04	0.68	0.15	0.15	0.64	0.14	0.26	1.2
	5	2.3	0.25	0.04	0.5	0.13	0.14	0.61	0.18	0.24	0.72
eother	1	0	0.15	0.04	2.36	0.03	4.16	0.26	0.49	1.79	1.79
	2	0.43	0.41	0.07	21.78	0.13	0.99	0.36	1.8	1.5	3.97
	3	0.26	0.56	0.06	0.49	0.19	0.26	0.53	0.97	0.62	12.45
	4	0.08	0.19	0.03	0.25	0.08	0.04	0.33	0.16	0.27	3.02
	5	0.07	0.17	0.03	0.23	0.1	0.06	0.3	0.14	0.22	5.37
emis	1	0.02	0.32	0.03	0.21	0.23	0.18	1.05	4.21	0.83	2.94
	2	0.76	0.56	0.09	0.5	0.09	2.48	0.4	0.41	0.59	0.61
	3	0.6	0.54	0.13	0.43	0.12	34.08	1.6	0.35	0.4	0.72
	4	0.09	0.11	0.03	0.24	0.06	0.59	0.12	0.11	0.14	0.33
	5	0.11	0.13	0.03	0.18	0.06	1.79	0.1	0.15	0.14	0.31

5 Economic gains from global cooperation in fulfilling climate pledges³²

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Abstract

Mitigation of CO₂ emissions is a global public good that imposes different regional economic costs. We assess the distributional effects of cooperative versus non-cooperative CO₂ markets to fulfil the Nationally Determined Contributions (NDCs), considering different CO₂ permit allocation rules in cooperative markets. We employ a global computable general equilibrium model based on the GTAP-9 database and the add-on GTAP-Power database. Our results show the resulting winners and losers under different policy scenarios with different permit allocation rules. We see that in 2030, we can obtain gains as high as \$106 billion from global cooperation in CO₂ markets. A cooperative CO₂ permit market with equal per capita allowances results in considerable monetary transfers from high per capita emission regions to low per capita emission regions. In per capita terms, these transfers are comparable to the Official Development Assistance (ODA) transfers. We also disaggregate the mitigation costs into direct and indirect shares. For the energy-exporting regions, the largest cost component is unambiguously the indirect mitigation costs.

Keywords: Nationally Determined Contributions; Carbon Egalitarianism; International Climate Agreements; General Equilibrium; GTAP Power; Article 6

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5.1 Introduction

It is widely recognized that climate change is caused by anthropogenic interference with the Earth's climate system and will have a massive impact on the environment, i.e., it will affect precipitation, temperatures, weather patterns, sea levels, acidity, and biodiversity (IPCC, 2014). Of particular concern is that climate change is expected to have disproportionate effects on regions where severe poverty is already widespread. Therefore, social justice and equity are considered core principles of 'climate-resilient development pathways for transformational social change' (Roy et al., 2018).

Starting from the experiences with the Kyoto Protocol, it has been clear that reaching an effective international climate agreement is complex due to international politics. The Kyoto Protocol was a top-down agreement meaning that the global emission reduction target was set. Subsequently, countries negotiated on how this global target would be distributed among them. Unlike this approach, the member states of the Paris Agreement followed bottom-up negotiations, where countries voluntarily committed to targets, formally known as (Intended) Nationally Determined Contributions (NDCs), without a pre-determined global emission reduction target. Additionally, under Article 6 of the Paris Agreement, countries were also encouraged '...to pursue voluntary cooperation in the implementation of their nationally determined contributions to allow for higher ambition in their mitigation and adaptation actions and to promote sustainable development and environmental integrity' (UNFCCC, 2015).

In the literature, studies that analysed the economic impacts of different emission reduction targets have shown that potential gains could be achieved by cooperation between countries. A cross-model review conducted by Hof et al. (2009) concludes that across literature, a fragmented regime is costlier than a universal regime even though a fragmented regime with 'a coalition of the willing' is more likely to be politically feasible. In the context of the first NDC targets pledged by countries, modelling studies (like Akimoto et al. (2017), Aldy et al. (2016), Aldy et al. (2017), Dai et al. (2017), Fujimori et al. (2016), Hof et al. (2017), Liu et al. (2020) and Vandyck et al. (2016)) have estimated regional carbon prices and Gross Domestic Product (GDP) impacts of fulfilling the NDC targets. Akimoto et al. (2017) and Fujimori et al. (2016), quantified the gains from cooperative action by modelling scenarios with and without cooperation. Fujimori et al. (2016) use the AIM-CGE model and estimate the gain in global GDP from cooperation to be 0.3 percentage points higher than unilateral action by countries. Akimoto et al. (2017) use the DNE21+ model and estimate that the global GDP losses would be reduced by 0.12 percentage points if countries cooperated to meet the NDC targets. In

contrast to both Akimoto et al. (2017) and Hof et al. (2017), we derive national abatement costs in a general equilibrium framework and thus, take spill-over effects between countries resulting from trade into account. Akimoto et al. (2017) and Hof et al. (2017) estimate only direct national abatement costs, e.g., national costs induced by emission cuts in their own country, while indirect abatement costs resulting from emission cuts in other countries are neglected.

Studies have also quantified how regional targets differ under different effort-sharing approaches. The stylized practice for modelling global cooperation is through an international emissions trading scheme (ETS). For designing an ETS, a fundamental question is related to the regional distribution of emission permits. Since we model a social justice scenario with full global cooperation under the assumptions of carbon egalitarianism, the allocation of permit rights is of interest to us. Höhne et al. (2014) present a cross-study comparison of 40 studies using seven categories of effort sharing methods based on equity principles of responsibility, equality, and capability. They conclude that targets based on equity principles and equal per capita emission rights lead to stricter emission reductions in OECD³³ countries and, in some cases, even negative permits in 2030 relative to 2010 emission levels. Höhne et al. (2014) also see that there could be large monetary transfers between regions in a global, cost-effective case if 'equal cumulative per capita emissions' and 'responsibility, capability and need' are used for effort sharing. Van den Berg et al. (2020) analyse the implication of a wide range of effort-sharing approaches on national emission pathways. While Van den Berg et al. (2020) focus on the impact of different effort sharing approaches on national emissions pathways, they do not yet include analysis of the impact on abatement costs and national shares in total abatement costs. Compared to Van den Berg et al. (2020), our paper focuses on national and total abatement costs and the impact that different economic mechanisms to implement NDC have on them.

Against this background, our paper aims to analyse the economic impacts of cooperative and non-cooperative action in reaching the initial NDC targets, considering different CO₂ permit allocation rules in cooperative markets. We provide a general equilibrium analysis of regional and sectoral costs and benefits, CO₂ permit allocations, and the monetary transfers that would result from the three different policy scenarios. We contribute to the existing literature that estimates the gains of cooperation by including the national and international cost spill-overs through the CGE framework. Moreover, we also contribute to the literature on the impact of

33 Here OECD countries consist of North America, Western Europe, Japan, Australia, and New Zealand.

different effort-sharing approaches by calculating the abatement costs in the CGE framework under two effort-sharing approaches, namely allocating permit rights based on national shares in emission reduction pledges versus allocating permit rights based on national shares in total population.

The rest of the paper is organized as follows. Section 5.2 describes the DART model. Section 5.3 defines the scenarios, followed by the analysis of the results in Section 5.4. Finally, we conclude with a discussion of the results in Section 5.5.

5.2 Methodology

5.2.1 Model description

The CGE setup is a unique framework that incorporates the interlinkages between different sectors within an economy and other economies through international trade. Such a design can holistically evaluate the impacts of policies ex-ante, and, therefore, the CGE approach is widely used when informing policymakers. The Dynamic Applied Regional Trade (DART) model is a numerical multi-sectoral, multi-regional recursive dynamic CGE model and has been applied to study international climate policies (e.g., Peterson & Klepper, 2007; Weitzel, Hübler, & Peterson, 2012) and biofuel policies (Calzadilla et al., 2014). The model is based on the GTAP-9 database (Aguiar, Narayanan, & McDougall, 2016).

Our study focuses on assessing the impact of climate policies through CO₂ pricing, and such policies typically have direct implications for the energy sectors. Therefore, we use the GTAP-Power supplementary database (Peters, 2016), which provides comprehensive data about different technologies in the power sector and consists of five types of renewable and three types of fossil-based technologies. To our knowledge, this is the first study that uses the GTAP-Power database to conduct such an analysis thus, adding novelty to our results. The GTAP-power database differentiates between the baseload and peak load for gas, oil, and hydro technologies. Our study aggregates the base and peak load technologies for each of these three sectors and does not differentiate between them. For this study, we aggregate the original dataset to 20 sectors and 24 regions as listed in and Table 5.3A and Table 5.4A in Appendix 5.7. Further, since we want to model climate policies, data on CO₂ emissions is also included in DART, which captures the emissions generated by the burning of fossil fuels for energy use in production and consumption activities. In the 2011 (base year of GTAP9 database), CO₂ emissions from the use of fossils account for about 71% of all GHG emissions.

With regard to the modelling of emissions in DART, we only consider CO₂ emissions from burning fossil fuels and exclude other sources of GHG emissions like emissions from LULUCF, GHGs other than CO₂ and GHG emissions from production processes. Naturally, to maintain consistency in our analysis the CO₂ mitigation targets used in our policy scenarios exclude LULUCF pledges made by countries (details in Section 5.2.2). The exclusion of the other GHGs reduces mitigation flexibility in our model since multi-gas flexibility lowers abatement costs in regions (Nachtigall, Ellis, Peterson, & Thube, 2021). Furthermore, the omission of process emissions could lead to an over-estimation of abatement costs from certain sectors (like cement) where emissions from production processes are high though the potential bias depends on the relative share of CO₂ emissions that have been ignored.

The core structure of the DART version used in this paper is identical to the previous studies (Klepper, Peterson, & Springer, 2003; Springer, 1998). As in all CGE models, the DART model consists of behavioural equations that describe the economic behaviour of each agent in the model based on microeconomic theory. Identity equations impose constraints to ensure that supply matches demand in factor and commodity markets, and macro closure rules determine the macroeconomic equilibrium conditions of the model. DART is a recursive dynamic model, and the yearly static equilibria are linked by exogenous assumptions of population change, technological progress, savings, and capital depreciation. There are three primary factors of input; land, labour, and capital. Land is a homogenous input for the agricultural and forest sectors only.

Labour is determined exogenously in the model based on the forecasts from OECD (2019) for the regional working population. Capital is modelled as putty-clay such that new capital complements the existing sectoral capital and, new investments are distributed to sectors based on the efficiency of the existing capital. Savings rate as a share of GDP is exogenously defined based on the OECD (2019) projections. Trade is modelled under Armington assumptions meaning that regions are connected via bilateral trade flows, where domestic and foreign goods are imperfect substitutes and distinguished by country of origin. Armington trade elasticities³⁴ and all income elasticities are taken from the GTAP-9 (Aguiar et al., 2016). The time horizon of the model is up to 2030. The production in every sector is represented by a nested constant

³⁴ An upper limit of 12.8 is imposed on the Armington trade elasticity for sector GAS. Additionally, we assume CRU has identical trade elasticities as sector GAS. The rest of the trade elasticities are exactly as in the GTAP database.

elasticity of substitution (CES) function. The nesting of non-energy sectors and the power sector with updated elasticities are shown in Fig A.1 and Fig A.2 in Appendix 5.7, respectively.

5.2.2 Calculation of the NDCs

There are differences in how commitments are submitted by countries, e.g., through differences in the target year, target sectors, greenhouse gas coverage, conditionality on financial and technological support, and the reference emission pathway (King & van den Bergh, 2019). Moreover, the NDCs have been framed relative to a diverse set of benchmarks – base year, GHG coverage, sector and source-specific targets, and target years. This forms a challenge when defining consistent reduction targets by country to be used for modelling. Different approaches have been used to aggregate these commitments to a single regional emission reduction target and we use the NDC targets as calculated in Böhringer et al. (2021), which is based on the approach proposed in Kitous et al. (2016). In essence, the aggregation of commitments is done as follows.

Kitous et al. (2016) convert all NDC targets for the energy sector (including renewable targets and sectoral targets) into policy measures using an energy system model. Furthermore, for countries that have pledged a GHG target, they calculate the CO₂-only reduction targets using a correction factor. The NDC targets are calculated as the net CO₂ emission reductions that regions would experience if all the targets in the energy sector (excluding CO₂ changes from LULUCF) are implemented as policies. In our analysis, we use this net CO₂ reduction as the equivalent NDC target that is achieved with a uniform (regional or global) carbon price.

Other commitments like reducing emissions from land use change, specific targets for green technologies or reduction targets for non-CO₂ GHGs are not modelled in our study. Thus, the regional mitigation targets are shown in Table 5.2, and they correspond to the conditional NDC pledges as derived using Böhringer et al. (2021). In the rest of the paper, NDC targets refer to the first round of conditional NDC pledges committed by countries (i.e. before 2020).

5.3 Description of Scenarios

We define three policy scenarios in addition to the baseline. The policy scenarios differ in how climate policies are implemented and, thus, the implicit degree of cooperation between regions. The climate policies are enforced by imposing a CO₂ price on fossil fuels in production and consumption activities from 2021 onwards in all regions. The regional emission reduction goals are based on the emission reduction targets committed by countries in their NDC pledges

(UNFCCC, 2015). The total global emissions pathway is identical in the three policy scenarios, albeit with differences in the underlying fairness principle. By having the same global emission reduction across all the policy scenarios, the policy shocks in the scenarios remain comparable. This setup allows us to assess the distributional effects of costs across regions based on differences in cooperation between regions and permit allocation rules. Table 5.1 provides an overview of the scenarios.

Table 5.1: Overview of scenarios

	NDC targets	Global emission reduction in 2030 relative to BASE	Geographical coverage of permit market	Degree of cooperation
BASE	no	-	none	-
REG	yes	11.8%	Regional	No cooperation
GLOB	yes	11.8%	Global	Full cooperation
PERCAP	yes	11.8%	Global	Full cooperation with carbon egalitarianism

Scenario **BASE** acts as the reference against which outcomes from the policy scenarios are compared. Our baseline scenario carries forward the GTAP-9 base year data from 2011 until 2030 by including projections of important drivers such as population growth, savings rate, and labour growth taken from the OECD (2019) forecasts. The DART baseline scenario is calibrated to match the regional GDP growth rate from OECD (2019) and the regional CO₂ emissions growth rate from IEA (2018). Given that the results from the policy scenarios are compared to BASE, it is essential to understand the global and regional economic trends in BASE.

Regional GDP is increasing in all the world regions with different growth rates. Following OECD (2019), globally, GDP increases by 65% in 2030 relative to 2011. GDP growth is the highest in India and China and, lowest in Russia. Global population increases by 22% in 2030 relative to 2011, with the highest growth forecast in Sub-Saharan Africa. Global emissions increase by 20% from 2011-30 with regional differences. As a result, per capita emissions in 2030 vary between 0.5tCO₂ in Sub-Saharan Africa to 13.3tCO₂ in the USA. In the context of international commodity trade, in BASE the net exports of coal, gas, and crude oil increase by 30%, 24%, and 20%, respectively. The net exporters of energy are Sub-Saharan Africa, Canada, the Former Soviet Union (except Russia), Central- and South America, Middle East-North Africa, EFTA, and Russia. The baseline growth rates for the regional GDP, population, and emissions are shown in Table 5.5A in Appendix 5.7.

In scenario **REG**, we model the regional reductions in emissions based on NDCs by unilateral action through cost-optimal national CO₂ prices. A linear emission reduction pathway is calculated to reduce emissions from baseline values in 2021 to meet the target values in 2030 via an endogenously determined yearly regional CO₂ price.

In scenario **GLOB** the cooperative implementation of the NDCs is modelled via a global CO₂ permit market. We assume that the yearly regional permit rights between 2021-30 correspond to the regional emission reduction pathway as calculated in scenario REG. However, instead of regional CO₂ prices, there is a global permit market where regions trade, and the model endogenously determines the corresponding global CO₂ price.

Scenario **PERCAP** is an adaptation of the scenario **GLOB**. This scenario is based on the principle of carbon egalitarianism, which means that each individual has an equal right to emit CO₂. This assumption implies that from 2021 onwards, the yearly regional CO₂ emission rights are distributed in proportion to the regional population, such that the global emissions are reduced according to the cumulative NDC pledges of all regions. Therefore, this scenario also represents cooperative action by the regions, although with additional fairness because of the carbon egalitarianism assumption.

Unlike REG, in scenarios **COOP** and **PERCAP** the regions trade permits. Thus, the resulting regional emissions could differ from their NDC pathway. We expect that regions that sell emission permits reduce more emissions than their NDC targets, while the permit buying regions will reduce fewer emissions than their NDC. We assume there are no transaction costs for the allotment and trade of permits. Further, the regional revenues from the trade of permits are transferred to the representative consumer (public and private) as a lump sum amount.

5.4 Results

We continue discussing how the regional and sectoral impacts differ from the three different policy designs described above. In the presented results, real GDP changes are calculated in \$2011. Welfare impacts refer to percentage Hicks Equivalent Variation relative to BASE. All the results discussed are relative to the BASE scenario for the year 2030, and it also coincides with the time horizon of the NDC targets. The only difference in reporting the results arises in Fig 4, where accumulated discounted welfare values are shown for the policy duration, i.e., 2021-2030.

5.4.1 Impact on CO₂ prices and CO₂ market

As indicated in Section 5.3, the total global reduction in CO₂ emissions is the same across all the scenarios, while the regional emission cuts vary across the scenarios. Fig 1 shows the resulting CO₂ emission reduction and the emission allocated to each region according to the scenario assumptions. By design, the emission reductions under REG are identical to the regional emissions under the NDC pathway. Relative to BASE, the largest reductions are in Pacific Asian regions, EFTA, Benelux, and the Former Soviet Union (except Russia). At the same time Russia, Australia, New Zealand, and India have the lowest emission reduction targets. The corresponding regional CO₂ price required to achieve these regional emission reductions is shown in Table 5.2.

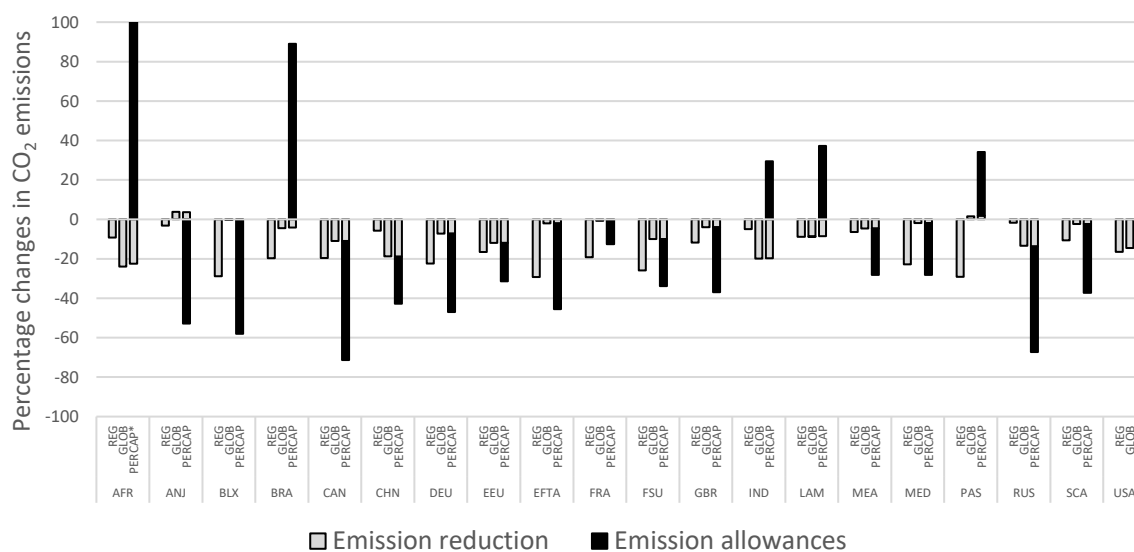
Compared to REG, costs regions either decrease or increase their net emissions reductions under GLOB and PERCAP depending on the regional mitigation. This implies that regions with regional CO₂ prices lower than the harmonized global CO₂ price (like China, India, Russia, Sub-Saharan Africa) mitigate more than their unilateral targets and sell the permit rights to regions with CO₂ prices higher than the global price. Regions with CO₂ prices above the global CO₂ price (like Central-South America and the Middle East and North Africa) can also sell permits to regions with even higher regional CO₂ prices. However, this would only happen if the regions with lower CO₂ prices cannot meet the permit demand. Generally, permit trade is beneficial to both the seller and buyer of permits and minimizes the total cost of mitigation while also achieving the global climate target. To understand which regions are the buyers and sellers of permits, we elaborate on the resulting CO₂ prices in REG and GLOB.

In 2030, CO₂ prices in scenario REG range from \$6.5/tCO₂ in Russia to \$236.4/tCO₂ in EFTA countries (see Table 5.2). The weighted average price of CO₂ in the EU is \$80.4/tCO₂, while the weighted global price is \$42/tCO₂³⁵. Under global permission markets, there is a single harmonized global price of CO₂ in GLOB and PERCAP. These prices are within the range of the regional prices and are equivalent to \$16.2/tCO₂ and \$16.3/tCO₂, respectively³⁶. Comparing the global CO₂ prices from GLOB and PERCAP with the weighted global CO₂ price from REG indicates that the CO₂ price needed for abating the same amount of global emissions is significantly lower when regions cooperate rather than when they act non-cooperatively.

35 The weighted global average price is calculated by weighing the regional CO₂ price of each region by the share of emission reduction in overall global emission reduction. A similar method is used for calculating the weighted average EU CO₂ price.

36 Though the quantity of global permits is identical in GLOB and PERCAP, the general equilibrium effects of income generated through permit trade differ. Thus, the CO₂ prices are similar but not identical in these two scenarios.

Figure 5.1: Allocated and realised CO₂ emission reductions as percentage changes relative to baseline in 2030. The allocated emissions in GLOB are the same as the emission reduction achieved in REG.



**Note that for AFR the allocated emission rights are higher in PERCAP relative to baseline by 619% in 2030 but to maintain the readability of the graph the y-axis is limited to 100. Regional abbreviations: AFR-Sub Saharan Africa, ANJ- Australia, New Zealand and Japan, BLX- Benelux, BRA- Brazil, CAN-Canada, CHN- China and Hong Kong, DEU- Germany, EFTA- European Free Trade Agreement members, FRA-France, FSU- Former Soviet Union (Except Russia), GBR- United Kingdom and Ireland, IND- India, LAM- Central- and South America, MEA- Middle East and North Africa, MED- Mediterranean Europe, PAS- Pacific Asia, RUS- Russia, SCA- Scandinavia, USA- the United States of America.*

To estimate the overall potential monetary gains from cooperation, we compare the total mitigation costs across the scenarios by multiplying the CO₂ prices and the total emissions abated at this price. In REG, the total global costs are the highest and amount to around \$172 billion in 2030 alone. Comparatively, the global costs are close to \$66 billion and therefore around 60% lower when regions cooperate in scenarios GLOB and PERCAP. This difference in the total mitigation costs is significant and highlights how Article 6 of the Paris Agreement could be a powerful tool for cost-efficient climate policy. If supported by all countries, cooperative action can reduce about \$106 billion in global costs in 2030. Possibly further gains can be generated from recycling the revenue to enhance mitigation efforts, leading to even further reductions in global emissions without incurring any additional costs. Studies like Edmonds et al. (2019) estimate that recycling cost savings towards enhancing pledges could lead to an additional global abatement of an additional 50%, approximately equivalent to about 5GtCO₂ in 2030. While global costs for climate policies are reduced with global permit markets, it does not necessarily reduce costs for single regions (see section 5.4.3).

Figure 5.2: Difference between allocated permits and observed emissions in scenario GLOB. Regions above the x-axis are sellers of permits and regions below the x-axis are buyers of permits.

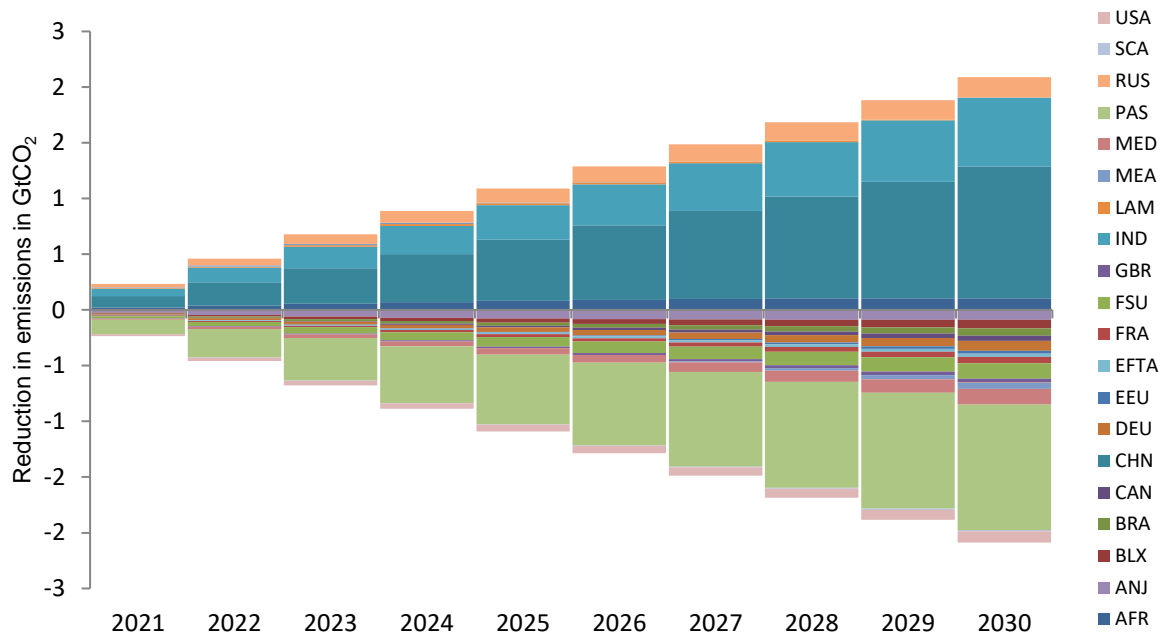
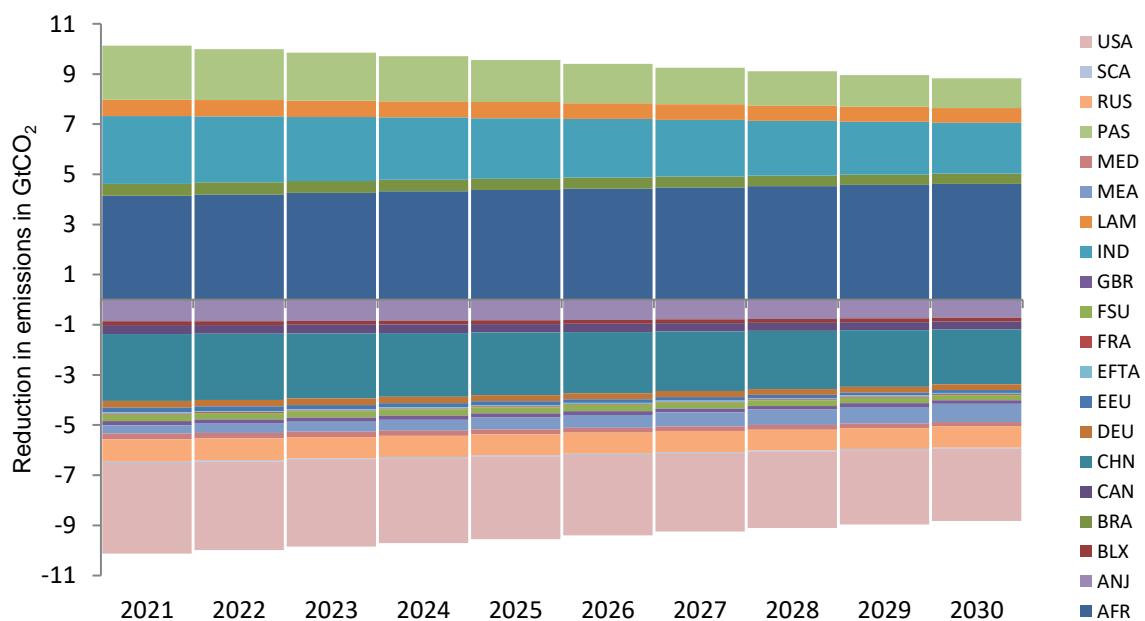


Figure 5.2 and Figure 5.3 show the difference between allocated permits and actual emissions across regions in scenario GLOB and PERCAP, respectively. The regions above the x-axis are sellers of permits, while regions below the x-axis are buyers of permits. In scenario GLOB, we typically see that regions with regional CO₂ prices lower than the global CO₂ price of \$16.2/tCO₂ are sellers of permits (Figure 5.2). Accordingly, China, India, Russia, and Sub-Saharan Africa are sellers of permits. From 2021-30, China is the largest seller of permits, and its market share remains close to 50% over all the years. Central- and South America and, Middle East and North Africa provide two interesting cases that switch from sellers to buyers of permits over time. With a starting CO₂ price of \$2.4/tCO₂ and \$2.8/tCO₂ in 2021 the regional CO₂ prices in these regions increase to \$20/tCO₂ and \$24/tCO₂, respectively. These prices happen to be the lowest prices among the countries with CO₂ prices above the global CO₂ price of \$16.2/tCO₂. Therefore, these two regions can trade at the fringe of the permit market by selling permits to regions with even higher regional CO₂ prices. Over the years, their market share shrinks from 5% to zero, and eventually, in 2030, both these regions are buyers of permits. The largest buyer of permits in GLOB is the Pacific Asia region which purchases close to 50% of the traded permits because it strongly increases emissions in BASE, a high emission reduction target (see Figure 5.1), and a relatively high CO₂ price of \$62/tCO₂. We observe a change in the grouping of buyers and sellers in scenario PERCAP from that in GLOB (see Figure 5.3). In PERCAP, the criterion for whether a region is a seller or buyer of permits indeed

directly depends on the annual rate of regional population growth and the average global per capita emissions. Thus, regions having higher per capita emissions than the global average are buyers of permits, while regions with per capita emissions lower than the global average are sellers of permits.

From 2021-30, the average global per capita emissions are reduced from 4.1tCO₂ to 3.5tCO₂ per year. Sub-Saharan Africa, Brazil, India, Central- and South America, and Pacific Asia are five regions that throughout this period have regional per capita emissions lower than the global average. As a result, these regions are sellers of permits in the PERCAP scenario. Sub-Saharan Africa has the highest growth in population from 2011-30 in the baseline. Therefore, according to the allocation rule, it also receives the highest share of permits each year from 2021 onwards. However, the emissions in Sub-Saharan Africa do not increase at the same rate, and as a result, it ends up being the largest seller of permits and consistently has a market share of about 50% each year.

Figure 5.3: Difference between allocated permits and observed emissions in scenario PERCAP. Regions above the x-axis are sellers of permits and regions below the x-axis are buyers of permits.



Brazil and Pacific Asia are buyers of permits in GLOB, while in PERCAP, they are sellers of permits because their per capita emissions are lower than the global average. An interesting turn is seen in China, which changes from being the largest seller of permits in scenario GLOB to being the second-largest buyer of permits by buying 30% of the total permits sold in scenario PERCAP because in 2030, China's per capita emissions are 6.1tCO₂. Therefore, to fulfil the

demand for emissions, China buys permits on the market. The largest buyer in PERCAP is unsurprisingly the USA since it has the highest per capita emissions of 11.2tCO₂ per year in 2030.

The results from scenarios GLOB and PERCAP show that market design and the fairness principle underlying the allocation of permits can lead to different outcomes regarding which regions buy or sell in permit trade. In addition, the global size of the market and the number of permits traded considerably varies based on the initial allocation of permits. In 2030, the total number of permits traded in scenario PERCAP embodies 8.8 billion tCO₂ which is more than four times what is traded in scenario GLOB. The resulting magnitude of the financial market arising from the permit trade in 2030 is around \$33.8 billion and \$144 billion in GLOB and PERCAP, respectively.

Apart from this, in scenario GLOB, the CO₂ market expands in size with each year because the historical trends of emissions are essentially carried forward in the future regional trends. Consequently, regions that emitted more than others until 2020 continue to do so by simply buying permits from regions that have emitted less in the past. On the contrary, the CO₂ market in scenario PERCAP contracts in size over the years because of the permit allocation mechanism. The less emission-intensive regions are typically the developing regions; therefore, they receive more emission permits in scenario PERCAP than in GLOB. Since the global CO₂ price remains the same in GLOB and PERCAP, the market size and the corresponding revenues from selling these permits are much higher in PERCAP than in GLOB. This increase in CO₂ revenues leads to welfare improvements in the permit selling regions. Therefore, over the years, we see an increase in permit retention by these sellers to meet domestic needs, leading to a relatively smaller permit market.

5.4.2 Global economic effects

Similar to the effects on CO₂ markets, the macroeconomic effects in the three policy scenarios also diverge. The global GDP is reduced by 0.13% (\$155.6 billion) in scenario REG, by 0.03% (\$55.7 billion) in scenario GLOB and by 0.04% (\$1.3 billion) in scenario PERCAP. Undoubtedly, the global losses in GDP are much lower when regions cooperate than when regions act non-cooperatively. In scenario REG, there is a contraction of the global production by 0.3%. On the contrary, in GLOB and PERCAP scenarios, global production increases by 0.1% and 0.01% despite reducing global CO₂ emissions by the same amount as in scenario REG. Correspondingly, the household expenditure sees losses of 0.2% in the REG scenario

with no effect under the GLOB scenario but gains of 0.6% in PERCAP. This is a key result highlighting that cooperation reduces global economic costs (in both GDP and welfare), and therefore, cooperation between regions is globally advantageous.

Expectedly, the presence of CO₂ prices affects the energy markets and alters the fuel mix of regions. As a result, producers either reduce the use of CO₂-intensive fuels or switch to less CO₂-intensive fuels. Switching to less CO₂-intensive fuels covers cases where producers reduce the CO₂ intensity of their fossil energy portfolio (e.g., from coal power to oil or gas power because oil and gas are less CO₂-intensive than coal) and when producers entirely replace fossil energy sources with renewables. These patterns in fuel switching are seen in the global production of fossil-fired power in different magnitude in the three policy scenarios.

The global production of coal decreases by 17-20% and that of gas by 5-8% across the three scenarios in 2030. Crude oil production falls by 0.3-0.8% across the scenarios. Production of fossil power falls by 17% globally in REG and 11% in GLOB and PERCAP scenarios. Within the energy sectors, there are reductions in coal and gas power, while increases in power from petroleum and coal products. Thus, the biggest burden of emission reduction is absorbed by coal because globally, on average, coal is the most CO₂-intensive fuel (considering end-of-pipe emissions only). The global renewable power production responds to the decrease in fossil production and increases production by 8% in the REG scenario and 5% in both GLOB and PERCAP. Within the renewable power sectors, Solar increases by 6-13%, wind by 8-10%, and other renewable technologies (biofuels, waste, geothermal and tidal technologies) by 9-16% in the three policy scenarios.

These global patterns described above cannot be generalized for each region simulated in DART. The impacts on different regions depend on several region-specific economic structures, and we discuss these in Section 5.4.3.

5.4.3 Regionally differentiated effects

Typically, the regional mitigation costs can be disentangled into two components; direct costs and indirect costs. Direct costs arise because regional CO₂ prices principally increase the (intermediate) input costs of energy, assuming the absence of pre-existing market distortions. The net direct costs depend significantly on the flexibility in the energy markets and the degree

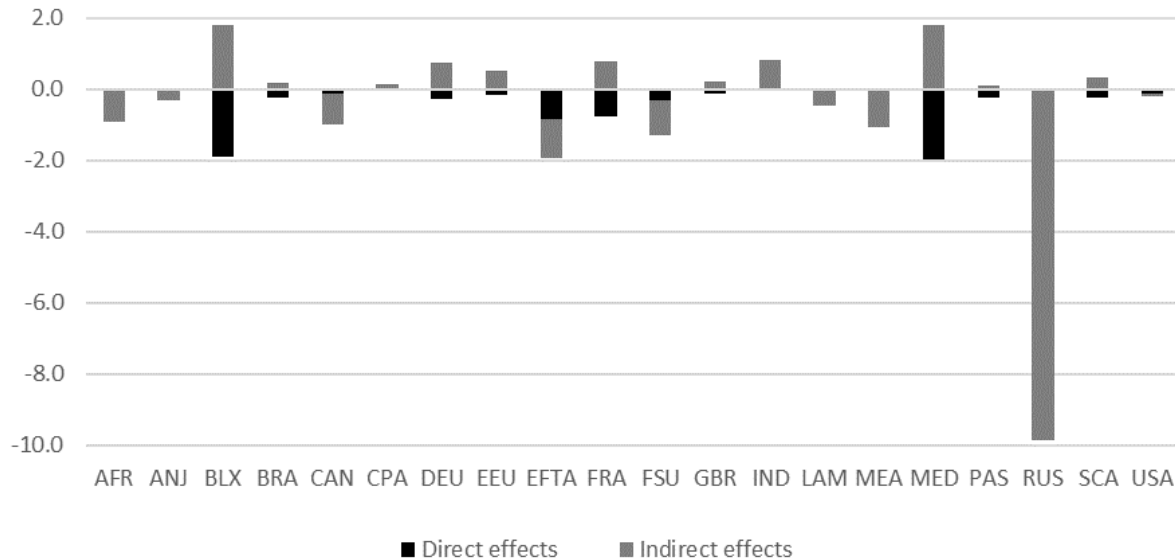
Table 5.2: Regional percentage changes in macroeconomic variables across scenarios relative to BASE in 2030.

	Allowances in 2030 (in GtCO ₂)		NDC target for 2030 (%)	CO ₂ price (per tCO ₂)	GDP (%)			Welfare (%)		Energy production (%)			
	GLOB	PERCAP	ALL	REG	REG	GLOB	PERCAP	REG	GLOB	PERCAP	REG	GLOB	PERCAP
AFR	654	5176	9.2	10.5	-0.7	-0.3	3.4	-1.6	-0.7	7.7	0.1	-2.5	-0.8
ANJ	1237	602	3.1	29.4	-0.1	-0.2	-0.3	-0.4	-0.6	-1.3	0.0	0.4	0.4
BLX	192	113	28.8	162.8	-0.2	-0.1	-0.1	-0.7	-0.2	-0.5	-8.6	-0.9	-0.8
BRA	345	812	19.7	72.9	-0.1	0.0	0.3	-0.3	-0.1	1.2	-2.8	-0.6	-0.6
CAN	423	151	19.6	30.1	-0.5	-0.3	-0.6	-1.8	-1.1	-2.0	-4.0	-2.3	-2.4
CHN	8599	5218	6.7	12.0	0.2	0.1	-0.4	0.2	0.2	-0.6	0.4	-0.9	-1.0
DEU	453	310	22.4	41.6	0.2	0.1	0.0	0.7	0.3	0.0	-2.2	-1.1	-1.1
EEU	484	398	16.5	25.5	0.2	0.0	-0.1	0.6	0.1	-0.1	-0.9	-0.7	-0.8
EFTA	75	58	29.2	236.4	-1.2	-0.4	-0.4	-4.3	-1.4	-1.4	-8.3	-0.8	-0.7
FRA	249	270	19.2	113.3	-0.1	0.0	0.1	-0.4	0.2	0.3	-6.0	-0.7	-0.7
FSU	643	574	25.8	34.6	-1.2	-0.7	-0.8	-2.6	-1.5	-1.8	-3.4	-1.3	-1.3
GBR	396	283	11.8	41.0	0.0	0.0	-0.1	0.1	0.0	-0.2	-0.9	-0.5	-0.5
IND	3937	5365	5.0	13.7	1.2	0.9	1.6	1.7	1.2	2.2	1.2	-0.3	0.0
LAM	1171	1763	8.9	20.4	-0.3	-0.2	0.2	-0.9	-0.4	0.4	-2.9	-2.6	-2.5
MEA	2882	2212	6.4	24.4	-1.0	-0.3	-0.5	-2.2	-0.7	-1.1	-2.9	-2.2	-2.3
MED	516	481	22.9	109.5	-0.2	0.0	0.0	-1.5	0.3	0.1	-4.6	-0.8	-0.9
PAS	2595	4915	29.2	62.3	-0.1	-0.2	0.5	-0.2	-0.4	1.0	-4.2	-0.8	-0.7
RUS	1531	510	1.7	6.5	-2.2	-0.8	-1.8	-19.4	-7.0	-15.2	-0.8	-2.0	-2.1
SCA	121	85	10.7	52.9	0.0	0.0	0.0	0.0	0.0	-0.1	-1.2	-0.4	-0.4
USA	4099	1309	16.6	19.1	-0.1	-0.1	-0.4	-0.4	-0.4	-1.4	-3.3	-3.2	-3.3
WORLD	30603	30603	11.8	42.0	-0.13	-0.05	-0.04	-0.32	-0.11	-0.02	-1.8	-1.3	-1.3

Note: The sensitivity of the results was checked by performing simulations with doubled and halved Armington elasticities. The key results of global gains from cooperation in GDP (between 0.09-0.12% in GLOB and between 0.01-0.02% in PERCAP) and welfare (between 0.2-0.3% in GLOB and between 0.08-0.13% in PERCAP) hold. Detailed results are available upon request from authors.

to which substitution is allowed between different energy sources. Indirect costs primarily arise from spill-over effects and their feedbacks between the domestic and international energy-related sectors. The regional CO₂ prices cause a reduction in the demand for global energy, which impacts the global prices of energy commodities³⁷. Depending on whether a region is an importer or exporter of energy commodities, the domestic production and traded (imports and exports) quantities of energy commodities would be impacted differently. The sum of these two components determines the net regional abatement cost.

Figure 5.4: Direct and indirect components of cumulated-discounted welfare in REG



We disentangle these two cost components for the net welfare changes in scenario REG (see Figure 5.4). We use the approach followed in Peterson and Weitzel (2016) to separate the direct and indirect costs. To calculate the direct costs, we implement the NDC target for each region while keeping the international prices faced by this region fixed to those in BASE. Such a modelling setup is equivalent to a region fulfilling its mitigation target while with no feedback on the international prices and gives us the direct mitigation cost component. The difference between the

³⁷ Global prices of commodities are calculated using the regional prices weighted by regional production quantities in 2030 relative to baseline. In REG, the global price of coal, gas, crude oil drops by 24.1%, 12.8%, and 2.4%, respectively. In GLOB the global prices of coal, gas, crude oil drops by 25.2%, 6.5%, and 0.5%, respectively, and in PERCAP they decrease by 24.9%, 6.1%, and 0%, respectively.

total costs and the direct costs gives us the indirect costs of mitigation.

In scenario REG, we see that the regions which are net exporters³⁸ of energy commodities in the baseline face losses in GDP and welfare with CO₂ prices. This is because both the regional characteristic of being a net exporter of energy and the levied CO₂ price for mitigation create a downward push on GDP. To understand this, we take the example of Russia. Russia has the lowest CO₂ price of \$7/tCO₂ and yet faces the highest regional GDP loss of 2.2% (\$48.1 billion) and the highest welfare loss of almost 20% (\$3.3 billion). However, from Figure 5.4, we see that almost all of the costs faced by Russia are rising from the indirect effects of mitigation, and the direct mitigation costs are marginal. This can be chiefly attributed to the high share of energy exports in the GDP of Russia. As a result, even though Russia has a relatively low mitigation target, the reduction in energy prices has a substantial impact on the Russian economy. Similarly, the energy-exporting regions also experience a bigger share of costs from changes in the international energy sector relative to the domestic emission reduction.

Different from the energy-exporting regions, there could either be gains or losses in the energy-importing regions because the two channels of impact could affect the opposite or same direction. Therefore, the net costs (or gains) are determined by the dominant channel in a region. Unlike in the energy-exporting countries in energy-importing countries, we see some regions gaining and others losing. On the one hand, we have regions with GDP gains like India³⁹, which has the highest GDP gains of 1.2% (\$71 billion), followed by 0.2% gains in both Eastern Europe (\$6 billion) and China (\$34 billion). Net welfare gains are also seen in these regions. With a low CO₂ price of \$14/tCO₂ in India, production increases by 0.7% (with a 1.2% increase in the energy sectors), and private consumption increases by 1.1%.

On the other hand, we have regions with GDP losses like France, the USA, and Brazil. For instance, France has a high CO₂ price of \$113/tCO₂. Therefore, energy production falls by 6%, with an overall drop of 1.9% in exports and 0.6% in imports. Thus, the cost of high CO₂ price

³⁸ The energy-exporting regions in the base data include AFR, CAN, FSU, LAM, MEA, EFTA, and RUS. The rest of the regions are net importers of energy.

³⁹ It should be highlighted that in our analysis, we observe gains for India in both direct and indirect cost components. We interpret this as India having tax distortions in the economy that are corrected by the CO₂ price, thus leading to welfare gains while emissions are reduced. Such an effect is not observed in any other region in our analysis.

outweighs the gains of being a net energy importer and overall, France faces a GDP loss of 0.1% (\$2.8 billion). In the energy-importing regions, we do not see a dominating cost component.

In the analysis of GLOB and PERCAP, we use the same two channels of impact; CO₂ price and global energy price. Besides, we now have a third channel stemming from the monetary transfers that arise from the trade of permits between regions. The significant difference between REG and GLOB comes from the CO₂ price that regions face wherein, unlike in REG all the regions have the same CO₂ price of \$16.2/t CO₂ in GLOB. We also observe a decrease in the prices of fossil commodities in GLOB, although relative to REG, the price drop is lesser for gas and crude oil and slightly higher for coal (see footnote 7).

From the discussions in section 5.4.2, we know that regions with CO₂ prices lower than \$16.2/tCO₂ in REG generate revenues by selling permits to regions with CO₂ prices higher than \$16.2/tCO₂ in REG. Under GLOB, all energy-exporting regions still experience losses in GDP; however, the magnitude of losses is reduced, mainly since energy prices fall less than the REG scenario. For example, the losses in Russia's GDP are reduced from -2.2% (\$48.1 billion) to -0.8% (\$17.5 billion). Russia is a seller of permits and gains about 0.1% of GDP (\$3 billion) from the permit market in 2030. Total production in Russia is reduced by 0.5% in GLOB, comparable to the 0.4% fall in REG. However, the sectoral components of total production activities are quite different in REG and GLOB. Given the comparatively higher CO₂ price in GLOB, the production of high energy input sectors like chemical, rubber, and plastic sectors, energy-intensive industry sectors⁴⁰, heavy and light industry sectors increase by a smaller amount compared to REG.

Among the energy-importing, France switches from losing GDP by 0.1% (\$2.8 billion) under REG to slightly gaining in GDP by 0.02% (\$1.1 billion) under GLOB. This happens because France faces one of the highest regional CO₂ prices in REG of \$113/tCO₂ and, therefore, benefits from the lower CO₂ price of \$16.2/tCO₂ in GLOB. Production of energy sectors falls by 0.7% (compared to 6% in REG), and total production remains unchanged relative to the baseline. Among the energy-importing countries, China is an example of a region that gains less in GDP in GLOB (0.1%; \$27.5 billion) than REG (0.2%; \$34.8 billion). China is a permit selling region in GLOB, and the monetary gains from the permit market add up to 0.1% of GDP in 2030. The input costs

⁴⁰ In DART, the energy-intensive sectors consist of mineral products, ferrous and other metals, and pulp and paper products.

of energy are higher in GLOB than REG since China faces a higher CO₂ price in GLOB. Therefore, we see a reduction in the total production in China by 0.2%. The largest reductions in production are in the energy-intensive industry (0.5%) and mobility sector (0.3%), with a reduction of 0.9% in the energy sectors. Comparatively, all these sectors increased production in REG because of the low CO₂ price in China.

In the PERCAP scenario, the losses and gains are distributed quite differently. Regions with a high population and low emissions per capita have the highest increases in GDP. GDP increases by 3.4% in Sub Sahara Africa and 1.6% in India than the baseline in 2030. These increases are predominantly driven by revenues from selling permits which amount to 2.5% of GDP in Sub-Saharan Africa (\$7.5 billion) and 0.5% in India (\$3.3 billion). With a substantial increase in consumption (2.1%), Sub-Saharan Africa increases net imports by 10%. It is, together with India (0.1%), the only region where total production rises under the PERCAP scenario (0.6%), mainly driven by the service sector (2%). Also, Central- and South American countries that lose GDP under the REG and GLOBAL scenarios have rising GDP values under PERCAP, since they benefit from selling emission permits due to relatively low emissions per capita (see Section 5.4.2).

In PERCAP, the highest GDP losses occur in regions with high per capita emissions and are net exporters of fossil fuels. For example, in Russia, an exporter of fossil fuels, we see GDP decline by 1.8%. This decrease is caused by the spending on permits (\$1.3 billion or 0.6% of GDP) and a fall in total production (0.7%) and net exports (0.7%). Net exports of coal decline by 19%, those of gas by 8%. China, Canada, and the USA also have high emissions per capita and experience a drop in GDP (0.6-0.4%), which are higher than the GLOB scenario with almost equal reductions in emissions. This difference can be explained by expenditures for permits, which are very small under the GLOB scenario, but amount to about 0.2% of their GDP under PERCAP and losses in production (0.2%-0.3%). In China, for example, reductions in domestic consumptions are not compensated by more exports of heavy and light industry products to Sub-Saharan Africa, such that GDP declines. Hence, we see the following effect in the Chinese economy: expenditures to buy permits lead to less consumption and less production, but an increase in the exports to regions that benefit from selling permits.

5.5 Conclusion and policy implication

This study calculates the global costs and their regional distribution for achieving the NDC targets under different assumptions on cooperation between regions. Our results show that in 2030 global costs are lowered by 60% when regions cooperate compared to when they act unilaterally. Article 6 of the Paris Agreement urges countries ‘to pursue voluntary cooperation in the implementation of their nationally determined contributions to allow for higher ambition’ (UNFCCC, 2015). However, this flexibility that regions can exploit in mitigation has yet to be seen widely in policy discussions. Evidently, with the significant reduction in economic costs that could be unlocked by allowing flexibility in emission mitigation, Article 6 of the Paris Agreement could play a key role in lowering the global costs of fulfilling the NDCs. It is expected that COP26, which is to be held in 2021, could be a decisive meeting in formulating the rules for cooperation through Article 6. Furthermore, as a part of the revision and resubmission of NDC targets so far 87 countries have submitted a new NDC target, 5 have proposed new targets while 72 have done neither⁴¹. Accordingly, if countries undertake cooperative action, the cost savings from the coordinated effort could be redirected and invested in enhanced mitigation action by boosting the revised NDC pledges, thereby providing economic and environmental gains.

Our results also highlight that the channels of costs are different for energy-exporting and energy-importing regions, leading to geopolitical tensions in ratcheting up the pledges. Notably, for energy-exporting countries, our results demonstrate that the dominant share of costs arises via the international energy market effects, and only a small share comes from the domestic abatement efforts. Thus, energy-exporting countries would stand to gain by discouraging the strengthening of pledges from the rest of the world. The bottom-up nature of the Paris Agreement could play a crucial role in avoiding such misalignment of global and regional incentives. In the Paris Agreement, unlike the previous top-down climate agreements, countries no longer have to negotiate within themselves to assign pledges to individual countries based on a commonly agreed global emission reduction target. Therefore, willing countries can circumvent the tedious political negotiations and voluntarily commit to higher pledges with limited influence of other countries.

We also show that the market design and distribution of emission permits matters and affects the regional gains and losses. The monetary transfers from the developed to the developing countries

⁴¹ Source: Climate Actions Tracker <https://climateactiontracker.org/climate-target-update-tracker/> (Accessed on 22 September 2021)

that are carried out under principles of carbon egalitarianism (scenario PERCAP) are substantial and comparable to the current monetary flows under Official Development Aid (ODA). For example, the per capita ODA received by Sub-Saharan Africa in 2018 is \$47 by the World Bank database (World Bank Database). According to the per capita monetary transfers from the simulated permit trading scheme in PERCAP it would receive \$51 in 2030. Therefore, if global justice is considered as a global public good, which similar to GHG mitigation, is underprovided, then the principle of carbon egalitarianism could promisingly combine an additional aspect to welfare, giving an important message for policymakers.

As mentioned in Section 5.2, our analysis focuses on CO₂ emissions resulting from the use of fossils for production and direct consumption activities which according to recent estimates account for about 73% of all GHG emissions (excluding LULUCF) in 2019 (Olivier & Peters, 2020). Hence, even though we do not have a complete coverage of CO₂ emissions from all sources and other GHG emissions we justifiably do account for a large share of CO₂ emissions which are our primary focus for this analysis. Additionally, the cost estimates from our study are derived under the assumption that regions use a single cost-optimal instrument (global or regional carbon price) to reach the equivalent CO₂ reduction while in practice countries might meet their targets with a policy mix. Thus, we expect our results to be a lower bound of costs of the analysed policies. In practical implementation, multiple policies would be implemented to reduce GHG emissions that would increase the costs and additional costs like would arise with their implementation (like setting up a regional carbon price or ETS, measuring and monitoring of emissions from different sectors), all of which are not considered in our model.

Lastly, as our analysis was done pre-Covid we have not considered the effect of the pandemic in our scenarios. There are updated forecasts in IEA,2021 related to the global demand for fossils, renewables and economic outcomes in the short-run until 2021. Since large uncertainties about the short- and long-term future of the recovery from Covid as well as the time-persistence of economic effects of the crisis still remain, we would see our results to hold under the assumptions that the recovery from the pandemic is not prolonged with long-lasting impacts and the global economy would return to the pre-Covid levels by 2030.

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5.7 Appendix

In all the production sectors in DART, capital (K) and labour (L) are nested together with a Cobb Douglas production function. The KL aggregate is then nested with energy with a CES production function with an elasticity of substitution of 0.5. The nesting of non-energy sectors is shown in Figure 5.5A and that of the power sector in Figure 5.6A.

Figure 5.5A: Nesting of non-energy sectors in DART

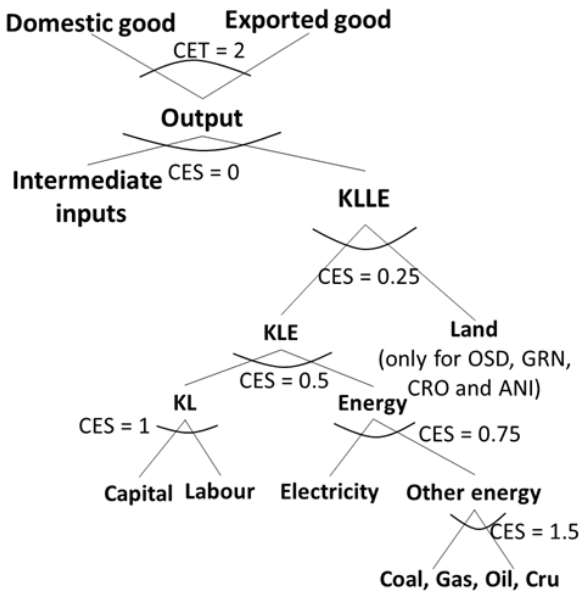


Figure 5.6A: Nesting of power sector in DART

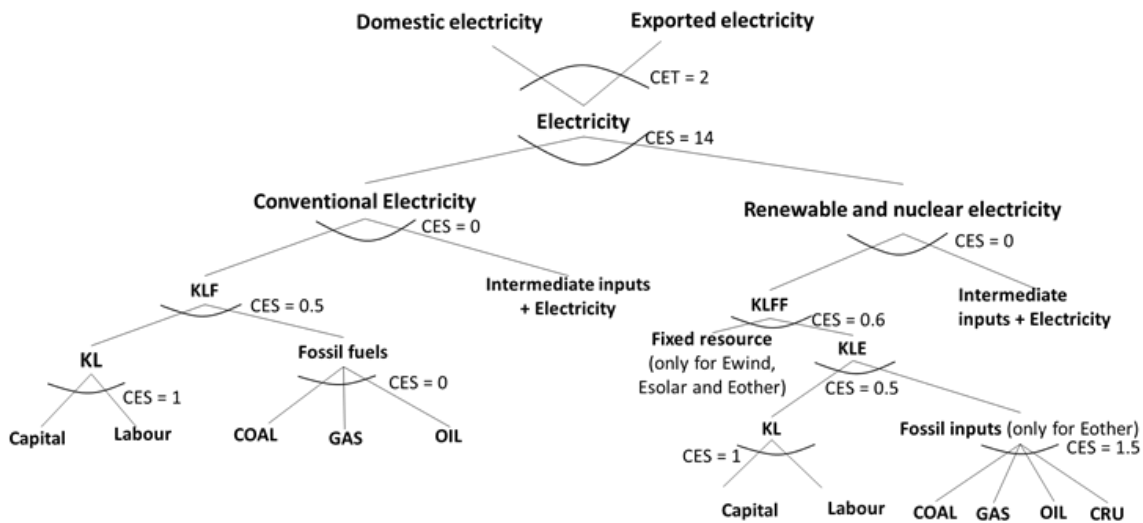


Table 5.3A: Description of regions in DART

DART regions (20)	Description
AFR	Sub Saharan Africa
ANJ	Australia, New Zealand and Japan
BLX	Belgium, Netherlands and Luxembourg
BRA	Brazil
CAN	Canada
CHN	China and Hong Kong
DEU	Germany
EEU	Czech Republic, Slovakia, Slovenia, Hungary, Estonia, Latvia, Lithuania, Bulgaria, Romania, Croatia, Austria, Poland
EFTA	EFTA and rest of the World: Norway, Iceland, Liechtenstein, Switzerland, Overseas Territories and Antarctica
FRA	France
FSU	Kazakhstan, Kyrgyzstan, Ukraine, Albania, Belarus, Armenia, Azerbaijan, Tajikistan, Turkmenistan, Uzbekistan, Georgia, Rest of Europe
GBR	United Kingdom, Ireland
IND	India
MED	Mediterranean Europe: Italy, Spain, Portugal, Malta, Greece, Cyprus
LAM	Central- and South America
MEA	Middle East, Northern Africa and Turkey
PAS	Pacific Asia
RUS	Russia
SCA	Sweden, Denmark and Finland
USA	USA

Table 5.4A: Description of sectors in DART

Non-Energy Products (12)		Energy Products (12)	
CRP	Chemical Products (rubber, plastic)	ENuclear	Nuclear power
ETS	Energy-intensive production	ESolar	Solar power
MOB	Mobility	EWind	Wind power
OLI	Other light industries	EHydro	Hydro power
OHI	Other heavy industries	ECoal	Coal-fired power
SVCS	Services	EGas	Gas-fired power
TND	Transmission and distribution	EOil	Petroleum and coal products for power
ANI	Animal Products	EOther	Biofuels, waste, geothermal and tidal technologies
GRN	Grains	COL	Coal
OSD	Oilseeds	OIL	Petroleum and coal products
CRO	rest of crops	GAS	Gas

RAGR	Rest agriculture and other processed food	CRU	Oil
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Table 5.5A: Baseline assumptions in DART

	Annual % GDP growth rate	Annual % CO₂ emissions growth rate	Per capita emissions in 2030 (in tCO₂)	Emissions in 2020 (in GtCO₂)	Emissions in 2030 (in GtCO₂)
AFR	3.8	1.6	0.5	635	720
ANJ	1.5	-0.5	7.4	1544	1278
BLX	1.7	-0.2	8.3	278	269
BRA	1.8	0.8	1.9	401	430
CAN	1.9	0.2	12.2	527	526
CHN	5.2	1.5	6.1	8667	9123
DEU	1.4	-0.4	6.6	635	584
EEU	2.3	-1.2	5.1	677	580
EFTA	1.7	-0.3	6.4	111	106
FRA	1.4	-0.3	4.0	330	309
FSU	3.4	0.1	5.3	907	867
GBR	2.1	-0.5	5.5	486	448
IND	6.5	4.9	2.7	2939	4145
LAM	2.5	0.6	2.6	1215	1285
MEA	3.6	2.2	4.9	2571	3081
MED	0.9	-1.7	4.9	799	669
PAS	4.1	2.7	2.6	2908	3664
RUS	0.6	-0.1	10.7	1516	1558
SCA	1.9	-0.6	5.6	150	135
USA	2.0	-0.2	13.1	5090	4912

6 Gains from linking the EU and Chinese ETS under different assumptions on restrictions, allowance endowments, and international trade⁴²

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Abstract

Linking the EU and Chinese Emission Trading Systems (ETS) increases the cost-efficiency of reaching greenhouse gas mitigation targets, but both partners will benefit – if at all – to different degrees. Using the global computable-general equilibrium (CGE) model DART Kiel, we evaluate the effects of linking ETS in combination with 1) restricted allowances trading, 2) adjusted allowance endowments to compensate China, and 3) altered Armington elasticities when Nationally Determined Contribution (NDC) targets are met. We find that generally, both partners benefit from linking their respective trading systems. Yet, while the EU prefers full linking, China favours restricted allowance trading. Adjusted allowance endowments that shift reduction obligations to the EU cannot sufficiently compensate China to make full linking as attractive as restricted trading. Gains associated with linking increase with higher Armington elasticities for China, but decrease for the EU. Overall, the EU and China favour differing options for linking ETS. Moreover, heterogeneous impacts across EU countries could cause dissent among EU regions, potentially increasing the difficulty of finding a linking solution favourable for all trading partners.

Keywords: Paris agreement, NDC, Emission trading, Linking ETS, China, EU

⁴² An older version of this paper is published online under the GTAP Conference Proceedings in 2021. Retrievable under: https://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=6244. We thank Duan Maosheng (Tsinghua University) and Sergey Paltsev (Massachusetts Institute of Technology) for their helpful comments on the first draft, and two anonymous reviewers for their equally helpful comments on the second draft. Funding: This work was supported by the German Federal Ministry of Education and Research (BMBF) [grant number 01LA1816A].

6.1 Introduction

The Paris Agreement abandoned the top-down approach of the Kyoto protocol, which defined an overall emission reduction target to be distributed among individual countries. Instead, following a bottom-up approach, individual countries are called upon to submit new pledges and emission reduction targets regularly, ideally adding up to a pre-determined global target (UNFCCC, 2020). Within the context of the Paris Agreement, these pledged emission reduction targets are termed *Nationally Determined Contributions (NDCs)*. Article 6 of the Paris Agreement (UNFCCC, 2015) outlines the possibility of reaching the NDCs through international cooperation, and includes the option of linking Emission Trading Systems (ETS) to do so. This is a recognized mechanism for increasing the cost-efficiency of international greenhouse gas mitigation (e.g. Alexeeva and Anger 2016, Nong and Siriwardana 2016, Fujimori et al. 2016), and the linking of national ETS is perceived as a fall-back option when international top-down approaches have failed (e.g. Ostrom 2010, Tuerk et al. 2009).

However, several studies find that linking existing ETS does not necessarily benefit all participating countries but can instead lead to welfare losses in the allowance selling region through terms-of-trade (ToT) effects (e.g. Flachsland et al. 2009). ToT is a country's ratio of export prices to import prices. In this context, ToT refers to the decreased competitiveness faced by allowance sellers as they connect to an ETS with a higher emission allowance price. Indeed, the allowance prices of all participating regions converge in the linked ETS, leading to an increase in the domestic allowance price of selling regions. As a consequence, the export prices of energy intensive goods increase, thereby decreasing the international competitiveness of allowance selling regions and potentially causing welfare loss. In Fujimori et al. (2016), several regions including China face negative economic impacts through the ToT effect when engaging in a global emission trading system compared to unilateral carbon pricing. Peterson and Weitzel (2016) find that transfer payments to energy exporters are necessary to counteract indirect market effects in a global ETS, with targets calibrated to a regionally equal loss of welfare. A similar situation applies to emission allowance exporters when ToT effects prevail over the revenue gains from selling emission allowances.

The EU and China have implemented the two largest ETS in the world. The EU-ETS was established in 2005 and covers energy intensive industries and the power sector. The Chinese ETS

officially started in February 2021 and applies to the power sector alone, with plans to further extend its coverage to the energy intensive industry sectors. Several studies have already analyzed the effects of linking a stylized EU and Chinese ETS. Hübler et al. (2014) find that China benefits marginally at best when a link to the EU ETS with restricted trading volume is established. In Liu and Wei (2016), both EU and China benefit from linking their ETS. Li et al. (2019) show that import quotas can avoid the negative effects of unrestricted linking between the EU and Chinese ETS. In case of full linking, China's net imports of chemicals, non-ferrous metals and refined oil increase, indicating a worsening of the ToT. If the number of permits traded is limited, Chinese exports (imports) of energy intensive goods increase (decrease), implying that a smaller tradeable permit quota protects the energy intensive industries in China. Gavard et al. (2016) model scenarios with a full link between the EU and Chinese ETS as well as allowance trading with different degrees of restrictions. They find that China suffers welfare loss when the ETS are fully linked, since the revenues from selling allowances do not offset the losses associated with the higher carbon prices induced by linking. Furthermore, China experiences welfare gains when the trading of allowances between the EU and China is limited. Welfare effects depend on the permit price (which decreases with a higher degree of linking) and on the traded volume (which increases with a higher degree of linking). Consequently, revenue from allowance selling and welfare effects are not linear (Gavard et al., 2016).

In this study, we use the computable-general equilibrium (CGE)-model DART Kiel to evaluate the drivers behind these partly contradicting results. We implement the EU ETS along with a disaggregated representation of the electricity sector. The model horizon for all scenarios is 2030, which is the target year of most currently submitted NDCs (UNFCCC, 2021). We establish a full link between the EU and Chinese ETS (aligned with its stylized current design plans) and develop a set of scenarios to analyse under which circumstances linking is most beneficial to the EU and/or China. These scenarios include 1) limits to traded allowance volume; 2) altering emission reduction targets in both regions so that EU has to abate more and China less, simulating transfer payments from EU to China; and 3) altering Armington trade elasticities⁴³. Thus, we address three main topics which are referred to in the literature: restricted trading, the opportunity for transfer

⁴³ Armington trade elasticities describe the substitutability between a domestically produced good and an imported good. With higher Armington elasticities, domestic goods can be substituted by imported goods more easily; thus, higher Armington elasticities can be interpreted as more trade openness.

payments (modelled as adjusted allowance endowments), and ToT effects.

Our study is part of a broader cross-model comparison study of the Energy Modelling Forum which is denoted “EMF36 - Carbon Pricing after Paris” and summarized in Böhringer et al. (2021). We add to the existing literature by systematically addressing the problem of unequal gains from ETS linking between allowance buyer and allowance seller. This topic has been addressed by a number of papers, albeit with diverse results. To the best of our knowledge, this study is the first to conduct a systematic analysis of how different measures affect these inequalities. We also at some points discuss inner-European heterogeneity stemming from different linking options and equalizing schemes.

This paper proceeds as follows. In section 6.2, we describe the model and our scenarios. In section 6.3 we present and discuss the modelling results, focusing on the gains from linking ETS in the EU and China. In section 6.4 we discuss our findings against the literature. Section 6.5 concludes.

6.2 Model description and scenario runs

The analysis in this paper is undertaken with the multi-regional, multi-sectoral, recursive-dynamic CGE model DART of the Kiel Institute for the World Economy (DART Kiel), which is designed to analyse climate and energy policies and calibrated to the GTAP9 power database (Aguilar et al. 2016). A non-technical description of the model can be found in Appendix 6.6. The regional disaggregation of the model is displayed in Table 6.1. The sectoral aggregation is in line with the EMF36 core scenarios (see Böhringer et al., 2021), but we further disaggregate the electricity sector into eight different technologies (coal, oil, gas, wind, solar, nuclear, and hydro based electricity and electricity based on other inputs) based on the GTAP9 Power database (Peters 2016). With the remaining four energy sectors (crude oil, refined oil products, coal, gas) and five production sectors (energy-intensive trade-exposed goods, transport, agriculture, other manufacturing, services) we model a total of 17 sectors.

Table 6.1: List of regions modelled in DART Kiel. Grey shading indicates EU ETS regions.

Region code	Countries / regions
CHN	China
FRA	France
GER	Germany
GBR	United Kingdom, Ireland

BLX	Belgium, Netherlands, Luxembourg
SEU	Italy, Spain, Portugal, Greece, Austria, Cyprus, Malta
SCA	Denmark, Finland, Sweden, Norway
EEU	Poland, Czech Republic, Slovakia, Slovenia, Hungary, Baltic States, Croatia, Romania, Bulgaria
REU	Rest of Europe (non-ETS): Switzerland, Albania, Belarus, Ukraine, Serbia, Rest of EFTA

The remaining 12 regions are in line with the EMF36 harmonization (Böhringer et al., 2021): USA, Canada, Russia, Japan, India, South Korea, Brazil, Australia + New Zealand, Other Americas, Other Asia, Middle East, Africa.

For the **Baseline** scenario, we calibrate DART Kiel to meet the GDP and CO₂-emissions projections of the World Energy Outlook 2018 (WEO; IEA 2018) in the year 2030. In this process we adjust constant annual regional total factor productivity growth rates and increase the GTAP Armington elasticities by a factor of 1.5 while allowing for a maximal value of 12 in order to achieve the given GDP growth rates⁴⁴. Table 6.8A in Appendix 6.6 displays key model parameters including Armington elasticities. To calibrate 2030 CO₂-emissions we adjust the autonomous energy efficiency (AEEI) improvements as well as the elasticity of substitution between fossil fuels and a fixed resource. The Baseline scenario also includes EU emission trading in the energy intensive industry sectors and the power sector subsequently referred to as the ETS-sectors (opposed to the remaining non-ETS sectors). Note that Rest of Europe (REU) does not participate in the EU ETS. Throughout this paper, we use the term “EU” as a synonym for “regions participating in the EU ETS”; hence, REU is excluded. By imposing a carbon price, the CO₂-emissions of the EU ETS sectors are calibrated to the emission targets proposed by the EU rather than the path outlined in IEA (2018)⁴⁵.

Next, we implement a policy scenario **NoLink**, in which China and the EU (and all other model regions) unilaterally reach their 2030 NDC emission reduction targets. DART Kiel only includes CO₂-emissions from the combustion of fossil fuels and we use the NDCs as quantified in Böhringer et al. (2021). They disaggregate the NDCs from Kitous et al. (2016) (weighted by 2030 emissions)

⁴⁴ This is necessary to achieve the given GDP growth in China, which turns out to be only possible in DART if there is enough flexibility for increased exports.

⁴⁵ The EU proposes the following targets: 21% reduction (against 2005 emissions) in 2020, 43% reduction in 2030; see https://ec.europa.eu/clima/policies/effort_en. This adjusted target for CO₂-emissions in ETS sectors is the only difference between our baseline and the harmonized EMF36 Baseline_WEO from Böhringer et al. (2021), as in the latter, the EU is not disaggregated into individual regions.

to the GTAP9 regional disaggregation to make them available for any desired aggregation. In our case, we aggregate the targets to the EU-regions in DART Kiel, which logically sum up to a joint EU target as shown in Table 6.2. The Chinese NDC is in reality formulated as an emission intensity target (emissions per unit of GDP) however similar to Gavard et al. (2016), Böhringer et al. (2021) translate this into an absolute target. Intensity targets are sensitive to the calibrated CO₂ and GDP path. Based on the calculations of Böhringer et al. (2021) in the case of China, this leads to zero emission reduction against the Baseline. However, given the current Chinese emission reduction efforts, this seems unrealistic. Thus, Böhringer et al. (2021) assume a 5% reduction against the Baseline, acknowledging that China has installed or will install at least moderate policies leading to effective carbon pricing. Though this approach ignores that changes in the GDP growth of China resulting from a linking of ETSS can affect the emission reduction efforts, any linking would probably include measures to ensure that it does not lead to extra emissions in China. Thus, our approach can be justified.

Table 6.2: CO₂-emission targets for EU regions and China relative to CO₂-emissions in the Baseline scenario in 2030

	CHN	FRA	GER	GBR	BLX	SEU	SCA	EEU	EU
NDC	-5%	-18%	-27%	-19%	-21%	-22%	-21%	-30%	-23%

We then run the model so that all NDC targets are reached by a uniform national carbon price covering all sectors. For China and the EU, we use the resulting emissions in the ETS sectors and non-ETS sectors as targets for the following scenarios. For the EU we use these targets also in the final NoLink scenario to model a joint EU ETS price and seven differing national prices to reach the non-ETS targets. This stylized approach makes our results comparable to other EMF36 results⁴⁶ but implies that we do not implement actual regional EU ETS allowance allocation.

We define three sets of scenarios to address our research questions. With the first set of scenarios (labeled “**restricted trading**”), we analyse the impacts of a joint EU - Chinese emissions trading scheme for the ETS sectors by restricting the traded allowance volume between the two ETSS. In the scenario with unrestricted allowance trading between the EU and Chinese ETS (labeled **FullLink**), 709 MtCO₂ are traded in 2030 between the EU and China. In nine additional scenarios,

⁴⁶ Except for the EU-ETS, the scenario NoLink is equivalent to the REF scenario in Böhringer et al. (2021), and the scenario FullLink is equivalent to the EURCHN scenario.

only 10%, 20%, ..., 90% of the 709 MtCO₂ can be traded between the two ETS. The impact of this restriction on individual EU regions is determined endogenously in the model through the EU ETS. While we acknowledge that – strictly speaking - neither NoLink nor FullLink meet the “restricted trading” criterion, we include both scenarios in the discussion of results from this set of scenarios, since the total of eleven scenarios (NoLink, FullLink, and nine restricted trading scenarios) allows us to create a gradient of the of traded allowance volumes.

In the second set of scenarios (labeled “**adjusted allowance endowments**”), we change the reduction targets of the EU and China by shifting more abatement obligations to the EU. This is to simulate transfer payments from the EU towards China, which could be used to partly offset economics losses in China due to linking of the two ETS. We run scenarios in which the respective EU emission target for the ETS sectors is increased by 10%, 20% ,..., 50%⁴⁷, and the respective Chinese target for the ETS sectors is decreased by the same amount of emissions so that joint reduction efforts remain constant. The adapted reduction targets are defined for each EU region, which adds up to EU-wide reductions due to inner-European emission trading. The adapted targets are applied to FullLink and half linking (restricted to 50% of the volume traded in FullLink; subsequently labelled as **HalfLink**). We do not model scenarios including adjusted allowance endowments without linking of ETS because the adjusted allowance endowments are implemented to equalize effects from linking. Thus, no adjustments are required in the absence of linking. Running FullLink and HalfLink scenarios for the five compensation scenarios altogether leads to 10 scenarios, which again allows the creation of a gradient of the strictness of the EU emission reduction target.

Previous studies have shown that climate policy analysis with CGE models is highly sensitive to the chosen trade elasticities (see e.g. Paltsev 2001). Therefore, with the third set of scenarios (labeled “**Armington elasticities**”), we analyze the impacts of different Armington elasticities since international trade is the main channel for international feedback effects influencing the gains from linking carbon markets of the EU and China. This allows for an in-depth analysis of ToT effects, which play a crucial role in the costs and benefits of emission trading regions. We run scenarios in which Armington elasticities are doubled and halved relative to the elasticities used

⁴⁷ Note that an increase of emission reduction targets means that the number of allowed emissions decreases: Hence, in this scenario allowed emissions in the EU decrease and those in China increase.

in the Baseline scenario. This change is applied either to all sectors or only to ETS sectors and for three linking situations: NoLink, FullLink, and HalfLink. It should be noted that altering Armington elasticities is not a policy scenario but changes the model settings. Thus, the Baseline scenario is simulated again with these four alternative Armington assumptions (halved in all sectors; halved in ETS sectors; doubled in ETS sectors; doubled in all sectors).

In conclusion, we obtain a total of 38 scenarios to include in our analysis, which are also listed in Table 6.3.

Table 6.3 Summary of scenario names and assumptions on traded allowance volume, Armington elasticities and emission reduction target.

No. of scen.	Scenario names	traded allowance volume	Armington assumption	emission reduction target
1	Baseline	0%	Standard	EU-ETS target
1	NoLink	0%	Standard	NDC
1	FullLink	100%	Standard	NDC
9	Link_X; X= 10, 20,..., 90)	X%	Standard	NDC
5	Link_full_comp_X; X= 10, 20, ...50	100%	Standard	NDC ± X%
5	Link_50_comp_X; X= 10, 20, ...50	50%	Standard	NDC ± X%
2	BAU_ / NoLink_Arm_halveETS	0%	standard /2 in ETS	-
2	BAU_ / NoLink_Arm_doubleETS	0%	standard *2 in ETS	-
2	BAU_ / NoLink_Arm_halveAllSec	0%	standard /2 in all sectors	-
2	BAU_ / NoLink_Arm_doubleAllSec	0%	standard *2 in all sectors	-
2	Link_full_ / Link_50_Arm_halveETS	50%	standard / 2 in EITE	NDC
2	Link_full_ / Link_50_Arm_doubleETS	50%	standard *2 in EITE	NDC
2	Link_full_ / Link_50_Arm_halveAllSec	50%	standard / 2 in all sectors	NDC
2	Link_full_ / Link_50_Arm_doubleAllSec	50%	standard *2 in all sectors	NDC

6.3 Description of results from scenario runs

In this section we sequentially discuss the key results of our three sets of scenarios, focusing on the implied efficiency gains from trading for both partners (EU and China) and the resulting burden-sharing for reaching the joint target. We also briefly discuss the implications for different EU countries/regions. Throughout the paper, the term “efficiency” refers to cost-efficiency, meaning that the climate policy is termed more efficient when the same emission reduction is reached with lower costs. As common in CGE literature, we use welfare measured in terms of Hicks Equivalent Variation (HEV) as a measure for economy-wide costs. HEV is a better measure

of national welfare than GDP since it takes price changes into account. It is defined as the change in income at current prices that would have the same effect on welfare as would the change in prices, with income unchanged. Note that DART Kiel does not include welfare effects resulting from (decreased) environmental damages through climate policy⁴⁸. All results displayed refer to the year 2030.

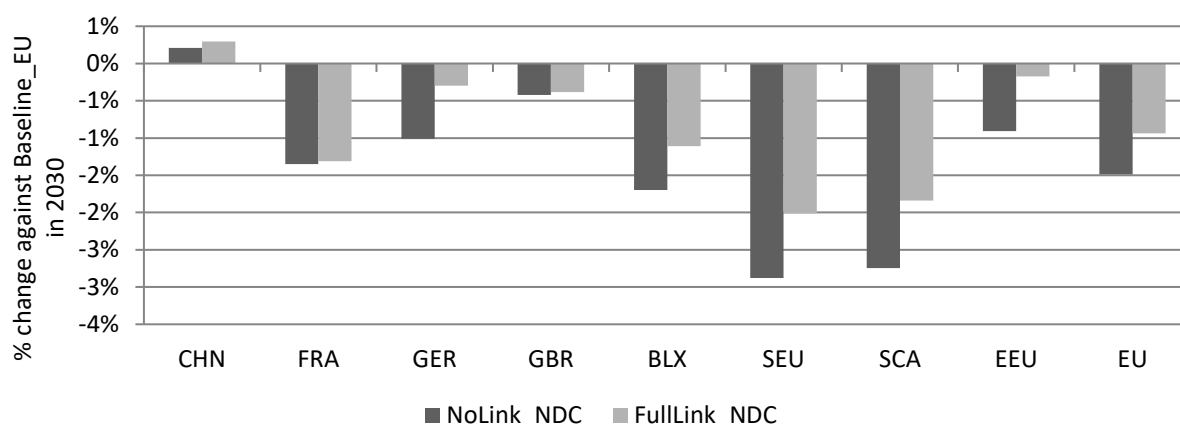
6.3.1 Core-linking scenarios

When we implement the described NDC emission targets, on the one hand, we see all EU regions lose in terms of welfare relative to the Baseline scenario, with the loss being larger without linking the EU ETS with the Chinese ETS (scenarios NoLink; Figure 6.1). China, on the other hand, receives welfare gains when NDCs are implemented globally. There are two reasons for this occurrence. First, as described by Peterson and Weitzel (2016), the demand for fossil fuels decreases as a consequence of global climate policy, bringing net prices of fossil fuels down. This is beneficial to energy importing regions such as China. Second, reduction targets in China are relatively low compared to the EU (see Table 6.2). Thus, China is relatively less affected by the introduction of the NDCs and consequently becomes more competitive compared to the EU and other regions with stricter targets.

When both regions link their ETS, the EU buys allowances covering a total of 709 MtCO₂ from China. While EU emissions in 2030 increase by 30.3% relative to NoLink, Chinese emissions decrease by 8.4% (see Table 6.4). This linking is beneficial for both the EU and China. Figure 6.1 reveals that not just the EU at large, but every EU region benefit from fully linking to the Chinese ETS, since the welfare costs relative to the baseline are lower in FullLink than it is in NoLink. Yet, Figure 6.1 also illustrates that the gains from linked emissions trading systems are significantly larger for most individual EU countries and certainly for the EU as a whole than they are for China. For instance, when moving from NoLink to FullLink, welfare improves by 0.08% in China, against 0.55% in the EU. Throughout the rest of this study, we analyze how our different assumptions affect these regionally unequal gains. In order to do so, we now turn towards the three sets of scenarios introduced in section 6.2.

⁴⁸ For all climate policy scenarios though, the global emission level is fixed, so that there is no difference in climate damages among these scenarios.

Figure 6.1: Welfare changes in NoLink and FullLink scenarios in 2030 relative to Baseline.



6.3.2 Restricted trading scenarios

Core results for the “restricted trading” scenarios are shown in Figure 6.2. The more trading is allowed, the lower the allowance price in the EU becomes, and the more CO₂ the EU emits. We see that the EU as whole benefits in terms of welfare not only from fully linking to the Chinese ETS, but also in all other “restricted trading” scenarios. The results for individual EU regions, which are not displayed here, reveal that the main sellers of allowances in the NoLink scenario within EU do not benefit under the highly restricted linking of EU and Chinese ETS. This arises from the fact that under linked ETS these regions lose part of their market to cheaper CO₂ allowances provided by China. Only for linked shares beyond 60% do all EU regions experience welfare gains, due to the benefits from lower carbon prices.

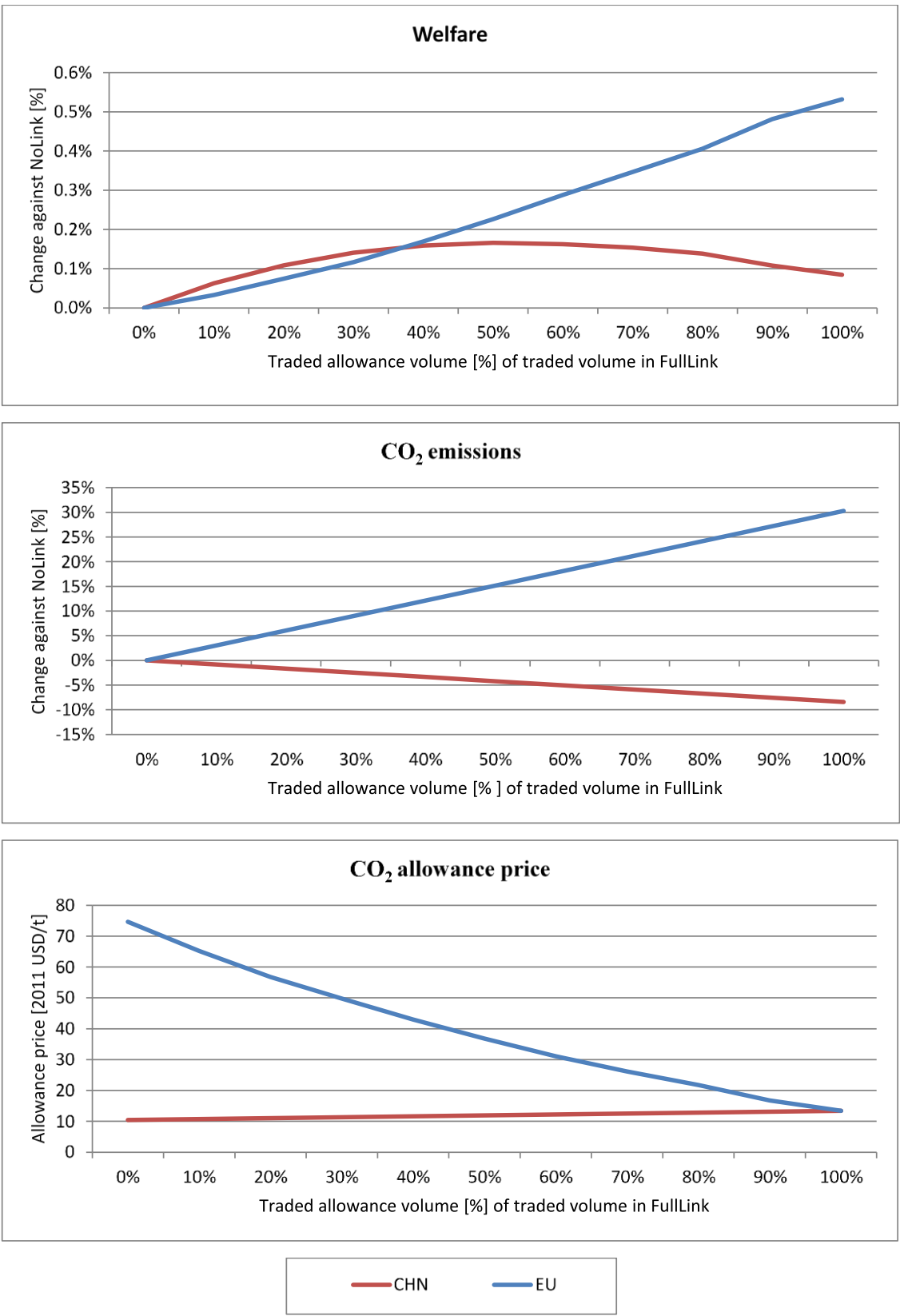
Table 6.4: Percentage and absolute change between NoLink and FullLink scenarios with NDC targets.

	Region-China	Region-EU
% change in welfare	0.08%	0.55%
% change in CO ₂ emissions	-8.4%	30.3%
% change in allowance price	29.0%	-82.0%
Difference in absolute price	3\$/tCO ₂	-61.2\$/tCO ₂

The absolute allowance price marks differences between NoLink and FullLink; e.g. the allowance price in the EU is 61.23 \$/tCO₂ lower in FullLink than it is in NoLink.

Different effects are observable in China. While we do not find a negative effect in welfare as a result of the linking of ETS, there is an optimum point where the trading of allowances is restricted

Figure 6.2: Main results of the “restricted trading” scenarios relative to NoLink in 2030.



to around 50% of the traded volume in scenarios with fully linked ETS⁴⁹. China's welfare thus forms an inverted U-shape when depicted as a function of the volume of allowance traded between China and the EU (see Figure 6.2). This inverted U-shape is driven by the same factors as in Gavard et al. (2016): Revenue that China gains from selling allowances is a function of the allowance price (which decreases with more linking) and the traded volume (which increases with more linking). The carbon prices converge in EU and China as the traded volume increases. Thus, carbon revenues generated with higher linking no longer compensate for the losses associated with sharing a stricter emission constraint with the EU. The relative changes in welfare against NoLink reach a maximum of 0.17% in China and 0.53% in the EU. As expected, the allowance price and CO₂ emissions in China develop contrary to that in the EU i.e. the allowance price increases with higher trading volume and the emissions decrease.

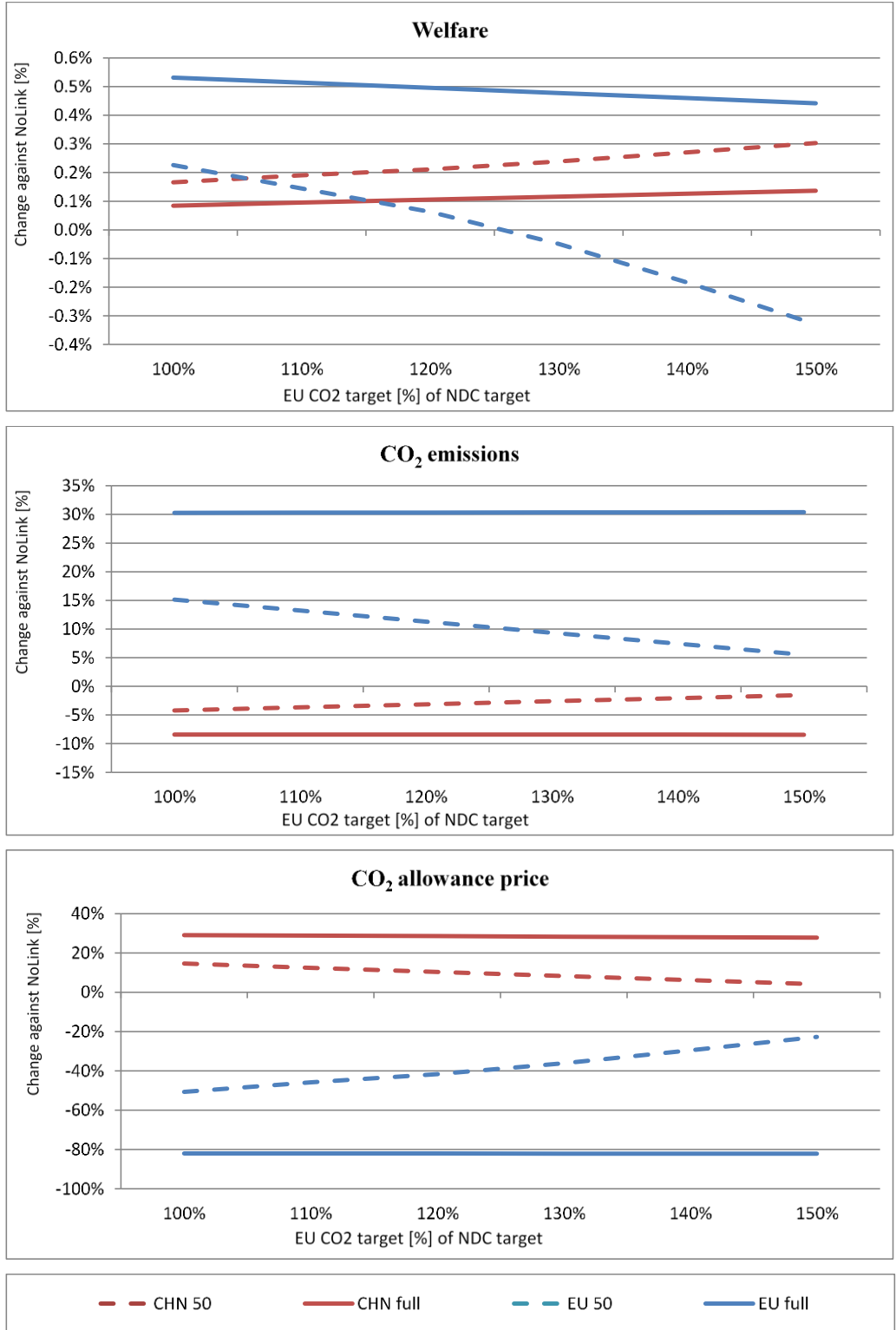
6.3.3 Adjusted endowments scenarios

For the “adjusted allowance endowment” scenarios, we compare the FullLink and HalfLink scenarios (the latter being optimal for China) to the NoLink scenario to analyze gains from allowance trading. Remember, that we model adjusted allowance endowments to the EU and Chinese ETS sectors to generate transfer payments, keeping the sum of ETS emissions of both regions constant overall compensation scenarios. For example, the scenario called “130%” assumes that the EU ETS CO₂ emission reduction target is tightened by 30% relative to the regular NDC i.e. instead of an emission reduction to 452 MtCO₂ (according to the regular NDC pledge) the target is now strengthened by 30% to get a reduction to 316 MtCO₂ (130%). Simultaneously, emission targets for the Chinese ETS sectors are loosened by the same amount, such that joint EU-Chinese ETS emissions remain constant. The main results of this comparison are displayed in Figure 6.3.

Both China's and the EU's total CO₂ emissions remain almost unchanged for all compensation scenarios relative to the NoLink scenario when ETS are fully linked, and the same holds for all the regions in the EU. Also, the allowance price in a fully linked ETS is almost independent of the level of compensation. Both emissions and allowance prices are unaffected, since the EU target becomes stricter by an amount equal to the weakening of the Chinese target, so that the EU simply

⁴⁹ This optimum at 50% is also the reason we introduce the „HalfLink” scenarios for the two following sets of scenarios.

Figure 6.3: Main results of the “adjusted endowments” scenarios relative to NoLink in 2030.



buys the extra demand for allowances from China in all scenarios and the income effects are negligible. This is also the reason why such a scenario is a good approximation of general transfer payments.

When allowance trading is limited to 50%, emissions in the EU decrease and emissions in China increase with higher compensation (relative to the NoLink scenario), since allowance trading cannot fully compensate for the differing allowance allocation. Thus, in this case, there are not only income effects from the adjusted allocation but also ToT effects. The CO₂ price in the EU is considerably higher and reaches 58\$/tCO₂ if emission trading is restricted compared to the price of 13\$/tCO₂ under FullLink trading. The allowance price in China decreases only slightly. Also, Chinese emissions are higher under HalfLink trading compared to FullLink. As a result, for both the EU and China, the ToT effects follow the same direction as the effects of adjusted endowments – China benefits from larger endowments not only through higher allowance revenues from a relaxation of its NDC targets but also from improved ToT. In turn, welfare in the EU decreases. As expected, effects are larger with higher compensations. In line with the ToT effects, the increase for China is higher if emission trading is restricted to 50% compared to unrestricted emission trading. The magnitude of this increase is comparable to the gains from “restricted trading” scenarios. For the EU, even a 50% increase in emission reductions (relative to the stated NDC target) is favorable in combination with a full link compared to a situation with no link. Though welfare gains from linking are reduced by the stricter targets in the EU, they are still positive compared to a situation without linking. Again, not all EU regions benefit equally. Only an increase of reduction targets up to 20% of emissions would be beneficial for all the EU regions in FullLink (relative to NoLink).

For HalfLink, where ToT effects negatively impact the EU, a maximum compensation of 20% of their emissions is beneficial in terms of aggregated EU welfare. Yet, it is also the case that some EU regions never gain in welfare, regardless of the size of endowment adjustments. For scenarios where the EU gains as a whole but not all individual EU regions do, internal distribution mechanisms need to be implemented to compensate the losing EU regions. While EU might consider to pay transfers to China under full trading in order to induce China to agree to a joint trading system, the resulting welfare gains in China are rather small. Under FullLink, adjusted allowance endowments of 50% increase welfare compared to NoLink by 0.1%. In the case of 20%

transfers under HalfLink (the maximum that is still beneficial for the EU as a whole), 0.2% are gained in terms of welfare.

6.3.4 Armington elasticities scenarios

While the two former sets of scenarios were concerned about different climate policy actions of the EU and China (restricting emissions trading / agreeing on transfers), the last set of scenarios is about different assumptions regarding the underlying trade elasticities. This implies that also the Baseline and the NoLink scenarios, which do not include further climate policies or linking of ETS, are affected. Before we turn to the gains from linking under different Armington elasticities, we investigate the effects of adjusting these elasticities.

Figure 6.4 shows the development of key variables for the Baseline and the NoLink scenarios relative to the corresponding scenarios with regular Armington elasticities. It turns out that Armington elasticities (i.e. restriction or relaxation of international trade) have a much stronger influence on welfare than a restriction of traded allowance volume or adjustments of allowance endowments. The relative changes against a baseline with regular Armington elasticities are in the range of -7% to 8% compared to changes below 1% for “restricted trading” scenarios. Effects are significantly stronger for adjusting all elasticities compared to only ETS elasticities. While the direction of welfare effects is the same in China, in the EU as a whole, and in all individual EU regions (all lose when Armington elasticities are reduced, and gain when they are increased, which is in line with the usual gains from trade), China is much more sensitive to these changes than the EU. This is driven mainly by a strong reaction in Chinese exports (-18% against regular Armington elasticities, when Armington elasticities of all sectors are reduced in the baseline and a 6% increase when Armington elasticities of all sectors are increased). Furthermore, Chinese imports decrease with increasing Armington elasticities. The EU exports hardly react to the altered Armington elasticities (minimal increase with higher elasticities), while imports into the EU increase with elasticities. Adjusting only ETS elasticities does not affect EU welfare.

For China, the relative changes in welfare correspond to stronger relative changes in emissions; as an example, a welfare increase of 8% in doubleAll corresponds to an increase in emissions of 12.5%. This is because China is a net exporter of emissions embodied in trade (see e.g. OECD statistics on emissions embodied in international trade <https://stats.oecd.org>). With increasing trade, their exported emissions increase. Also note that in halveAll China’s emissions decrease so

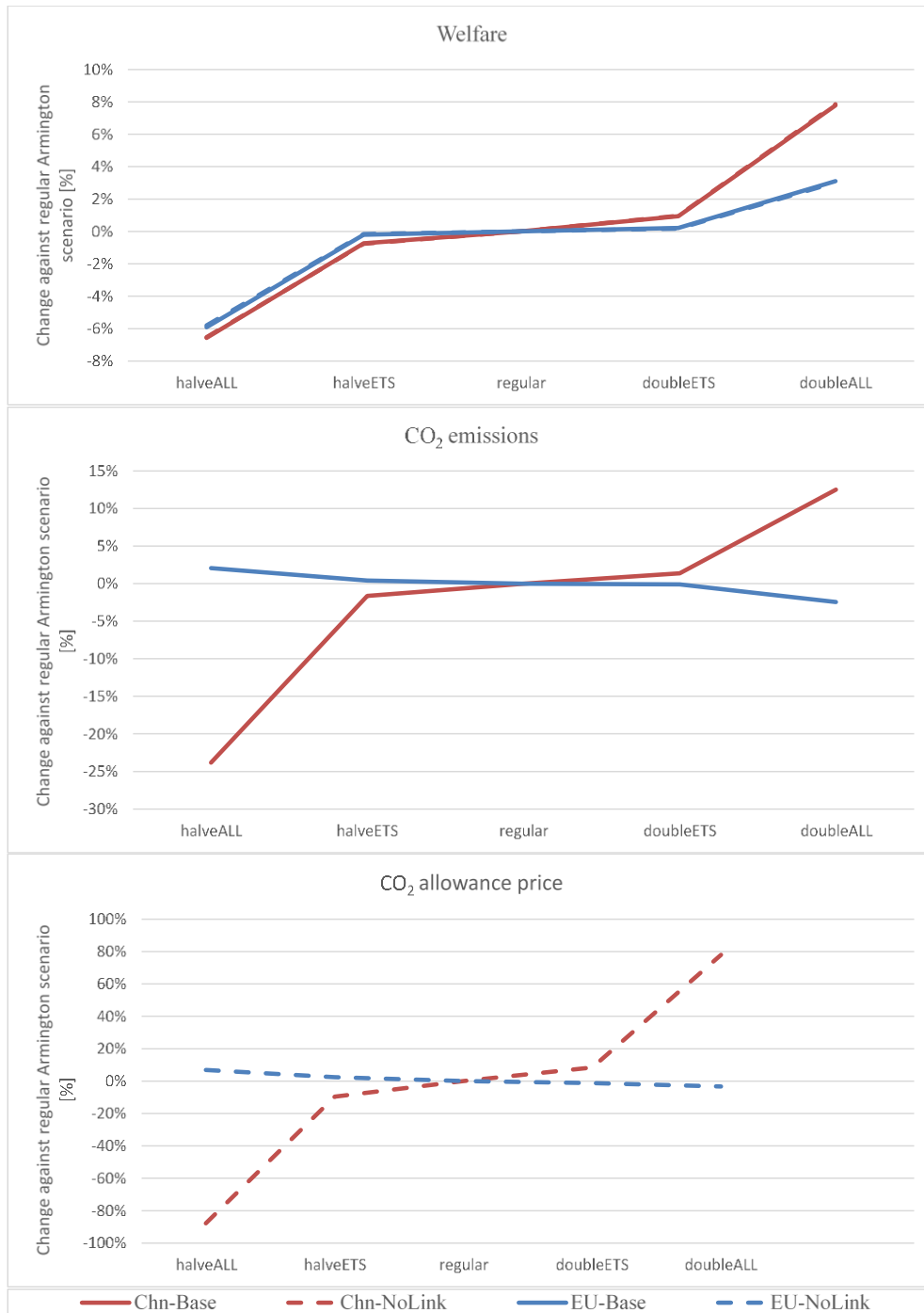
strongly that the carbon price reduced to 1.3\$/tCO₂ and strongly weakens the NDC target⁵⁰. For the EU, being a net importer of emissions embodied in trade, as well as for all EU regions, the effect is the opposite. As Armington elasticities increase, the EU outsources the production of emission intensive EITE sectors, so that EU emissions from ETS sectors decrease. As domestic production is replaced with imports, emissions decrease. When only the Armington elasticities for ETS sectors are doubled, the national emissions increase by a small amount because of a slight increase in production and emissions from the transport sector.

The effects for welfare in NoLink are almost identical to those in the Baseline for China, overall EU as well as the single EU regions. Overall CO₂ emissions remain unchanged, because both the EU and China reach their given targets themselves, regardless of Armington assumptions. The impact is now on carbon prices, which change in line with the emission changes in the baseline. Higher Armington elasticities in all the sectors (doubleAll) increase baseline emissions and carbon prices under NoLink in China and decrease them slightly in almost all EU regions. After explaining the effects of altering Armington assumptions on the Baseline and NoLink scenarios, we now turn to our focal question, which is how gains from linking ETS change for different trade elasticities. For this, we compare the FullLink and HalfLink scenarios relative to the respective (i.e., with the same Armington assumption) NoLink scenarios. The results of these comparisons are displayed in Figure 6.5.

As in the “restricted trading” and “adjusted allowance endowments” scenarios, also in all “Armington elasticities” scenarios China benefits significantly more when linking is restricted to 50% compared to full linking, while for the EU full linking is preferable. Both for China and the EU the effects of altered Armington elasticities only in ETS sectors are negligible (flat slope between halveETS and doubleETS in Figure 6.5), both in FullLink and HalfLink, because trade in ETS goods and trade in ETS emission allowances are substitutes, and the trading of allowances offsets effects from altered Armington elasticities. This argument is also supported by the lack of significant changes in emissions and allowance prices for half/doubleETS relative to the regular case. For HalfLink, also adjusting all Armington elasticities does not affect these results much. This is different for FullLink, where altered elasticities in all sectors (halve/doubleAll) have visible

⁵⁰ This result is in line with other modeling studies that show a non-binding NDC target for China (e.g., Liu and Wei 2016).

Figure 6.4: Implication of different “Armington elasticities” in 2030.

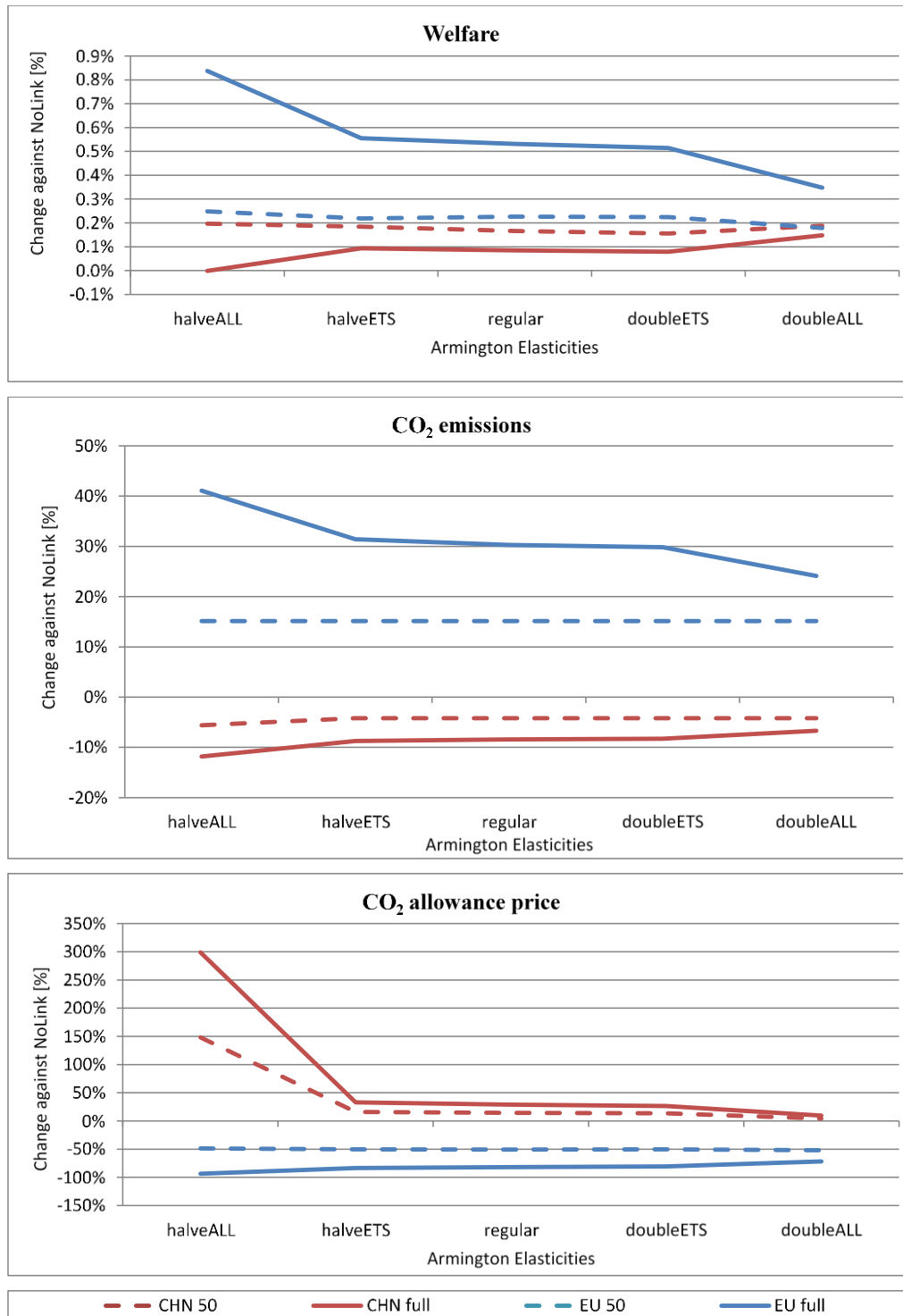


Note: No-climate policy is labelled as “Base”) and NoLink scenario as “NoLink” All changes are relative to the regular Armington scenario with the same linking assumption. Note that CO₂-emissions in NoLink are by design always equal to the regular case and are thus not shown. Also, there is no allowance price in the baseline.

effects. Now, trade in goods and trade in allowances are not full substitutes anymore, and the trend observed in the Baseline - higher Armington elasticities increase emissions in China and decrease emissions in the EU - is visible. Most importantly, higher Armington elasticities decrease the EU's gains from linking its ETS to the Chinese ETS, while they increase the gains for China. This makes the gains from trading more equal. On the contrary, lower Armington elasticities imply a more unequal distribution of the gains from trading. Under HalfLink this relationship is less pronounced, but one interesting result is that for HalfLink and doubleAll both China and EU gain welfare by the same percentage. When ETS are fully linked, all individual EU regions exhibit the same pattern as the EU. Yet, it can happen even in FullLink (in our setting in France), that with higher Armington elasticities in all sectors, linking decreases national welfare. In HalfLink, there is no Armington scenario where all individual EU regions concurrently gain in welfare relative to NoLink.

As for welfare, changes in CO₂ emissions are only significant, when we alter all elasticities (halve/doubleAll) and implement fully linked emission trading. In this case, CO₂ emissions in the EU and all of its individual regions decrease with higher Armington elasticities and the resulting increasing imports into the EU. This is because domestic production decreases and the EU imports more embodied carbon. For China, the opposite is true: emissions increase with higher Armington elasticities and resulting in increasing exports plus decreasing imports, depending also on the EU demand for allowances. As Chinese emissions from ETS sectors increase with higher Armington elasticities (the incentive for China to abate gets lower with increasing opportunities for exports), also the allowance price increases with higher Armington elasticities. This also leads to a higher allowance price in the fully linked EU-Chinese ETS. However, the CO₂ price in a joint EU-China ETS is still much lower than in NoLink or HalfLink scenarios, regardless of the Armington assumptions. When Armington elasticities are halved in all sectors and allowance trading with the EU is allowed (both half and full trade), the total CO₂ target in China is not binding anymore. ETS emissions are lower than in the scenario without allowance trading because China decreases its emissions to sell allowances to the EU. Also, emissions from non-ETS sectors, which in the scenario without allowance trading equalize these decreases, are low in the scenarios with the lowest Armington elasticities and do not equalize the reduced ETS emissions. Thus, the total combined CO₂ emissions of the EU and China are slightly lower in these scenarios than they are in the other scenarios, and the CO₂ price for non-ETS emissions in China becomes zero.

Figure 6.5: Main results of the “Armington elasticities” scenarios in 2030.



All changes are relative to the NoLink Scenario with the same Armington assumption; e.g. EU CO₂ emissions in a fully linked ETS (EU full) under “halfAll” Armington assumption are ca. 41% higher than in NoLink under “halfAll” Armington assumption.

6.4 Discussion

The purpose of this paper is to identify the gains associated with linking an EU and a Chinese ETS for the ETS sectors. Table 6.5 summarizes these gains for all sets of scenarios. We are aware that the changes are partly small, as is often the case for comparable scenarios (see also Böhringer et al., 2021), yet we see a clear pattern resulting from the policy interventions.

We find that in almost all scenarios, linking the EU and the Chinese ETS proves beneficial to both regions but to different degrees. In most scenarios, the EU gains more than China (0.53% rel. to 0.08% under NDC targets and full trading). Exceptions are seen if (shaded in grey in Table 6.5).

- allowance trade between EU and China is restricted to less than 30%;
- the EU transfers 10% or more of their allowances to China and if trading volume is restricted to 50%;
- under NDC targets Armington elasticities are doubled for all sectors, and trading volume is restricted to 50%.

Thus, although for the EU linking is generally beneficial, there are possibilities to distribute the gains in favour of China and thus avoid increasing welfare inequalities between the two regions. The scenario with halved Armington elasticities in all sectors and fully linked ETS yields no positive welfare impacts for China, which is the least favourable option for China. In the current situation where trade-barriers are clearly on the rise and voices are talking about de-globalization, such a scenario might become more likely.

Overall, our results indicate that the EU, should it aspire to link the EU ETS to the Chinese ETS, will have to take measures to make the linking of an EU and Chinese ETS more beneficial for China. This is true especially since the linking of ETS becomes more popular and other regions will compete for the cheap Chinese allowances. As with other studies, we find that a restriction of traded volume can significantly increase benefits for China. In our “restricted trading” scenarios we found China’s gains in welfare highest when allowance trading is restricted to 50% of the volume traded in the FullLink scenario. Even though the restricted trading scenario reduces the benefits for the EU compared to unrestricted linking, these are still significant and in relative terms about twice as high as those of China. Also, any allowance trading with China, be it restricted or not, is beneficial for the EU in terms of welfare.

Table 6.5: Gains (in terms of welfare relative to NoLink scenarios) from linking the EU and Chinese ETS for all scenarios

“Restricted trading” scenarios

Scenario \ Region	10	20	30	40	50	60	70	80	90	100
CHN	0.06%	0.11%	0.14%	0.16%	0.17%	0.16%	0.15%	0.14%	0.11%	0.08%
EU	0.03%	0.07%	0.12%	0.17%	0.23%	0.29%	0.35%	0.41%	0.48%	0.53%

“Adjusted allowance endowments” scenarios

Region	Scenario \ Linking	100%	110%	120%	130%	140%	150%
CHN	FullLink	0.08%	0.09%	0.11%	0.12%	0.13%	0.14%
	HalfLink	0.17%	0.19%	0.21%	0.24%	0.27%	0.30%
EU	FullLink	0.53%	0.51%	0.50%	0.48%	0.46%	0.44%
	HalfLink	0.23%	0.14%	0.06%	-0.05%	-0.18%	-0.33%

“Armington elasticities” scenarios

Region	Scenario \ Linking	halfALL	halfEITE	Regular	doubleEITE	doubleALL
CHN	FullLink	-0.001%	0.09%	0.08%	0.08%	0.15%
	HalfLink	0.20%	0.18%	0.17%	0.16%	0.19%
EU	FullLink	0.84%	0.56%	0.53%	0.51%	0.35%
	HalfLink	0.25%	0.22%	0.23%	0.22%	0.18%

Transfer payments from the EU to China are modelled through changing the allowance allocation to the EU and Chinese ETS sectors, keeping total emissions of both regions constant over all “adjusted endowments” scenarios. Thus, EU emission targets for the ETS sectors become stricter and Chinese emission targets for the ETS sectors become weaker by the same amount of emissions. Transfers through adjusted allowance endowments are most valuable to China under restricted trading, while the effects for China are minimal for full trading and thus, not a solution for more equalized welfare gains. For the EU, transfers through adjusted allowance endowments also imply little losses for full trading but come at a significant cost in case of restricted trading. In our scenarios, if more than 20% of allowances are transferred to China and trading is restricted to 50%, potential benefits from trading are eliminated. It should also be noted that – as mentioned in section 6.3 – adjusted allowance endowments are no longer a good representation of more general transfer payments under restricted trading, since the resulting emission reduction efforts change. Still, our

findings indicate that under restricted trading, transfer payments have little benefit for the EU. Thus, if at all, one should consider trade restrictions and adjusted allowance allocation as complements.

If we consider restricted trading on the one hand, and transfers through adjusted allowance endowments on the other hand, then China benefits more from the former compared to the latter. This holds even in the scenario where the EU transfers 50% of their allowances to China, which is a very extreme and politically unlikely scenario. Yet, even these high transfers through adjusted endowments would still be much more beneficial to the EU than restricting trading. The welfare gain is almost 50% higher when 50% of EU allowances are transferred to China than it is under HalfLink without such transfers. Hence, the potential trading partners prefer different linking scenarios: While the EU benefits more from full trading and would possibly pursue transfer payments as a measure to make linking more attractive to China, China will aim for a restriction of the trading volume. Analysing possible outcomes of such hypothetical negotiations from a political economy perspective could provide fruitful avenues for future studies.

Since trade in goods and trade in allowances are to some degree substitutes in the ETS sectors, gains from trading for both partners are higher for lower trade elasticities in ETS sectors. In times of increasing international trade restrictions, this is an important finding. Since China is more vulnerable to trade restrictions than the EU, linking could become more attractive under less open trading (i.e. lower Armington elasticities): welfare losses could be equalized to some degree by trading emission allowances when trading of goods is restricted. This is especially true for ETS sectors, since through emission trading losses arising from the trade restrictions in ETS sectors can be equalized. However, we find that the implications of altering Armington assumptions are much larger than the welfare gains which can be achieved by linking ETS. This stresses the potentially large negative effects of protectionism and trade conflicts.

Having a scenario with a negative welfare effect resulting from linking ETS (even though the loss is negligible) confirms the possibly ambiguous effects found in Flachslund et al. (2009). Unlike Fujimori et al. (2016), who found linking to cause negative welfare effects for China, and excepting the scenario mentioned above, linking is beneficial in all scenarios considered in our study. However, Fujimori et al. (2016) analysed a globally linked ETS, not just a link between China and the EU. Hübler et al. (2014) do evaluate a link between China and the EU for a case of restricted

linking⁵¹. Similar to our study, they also find positive welfare effects for China in all but one scenario, albeit rather small ones (about 0.1 percentage point lower welfare loss with linking, relative to a BAU without climate policy). Also in Liu and Wei (2016) linking ETS between the EU and China is for both regions always preferable to a comparable situation with separate ETS. They highlight the fact that the EU always favours a different scenario than China, which also holds true for most of our scenarios, where the EU always favours full linking over restricted linking, whereas the opposite is true for China. Thus, should a link between the EU and Chinese ETS be aspired, the actual design would have to be negotiated carefully. While our results differ from those in Gavard et al. (2016) in that unrestricted allowance trading is not beneficial in their study, the inverted U-shape we find for China's welfare under different degrees of linking (see Figure 6.2) is well in line with their finding of a non-linear relationship between the degree of linking and welfare effect. In Li et al. (2019), the authors find that in terms of welfare, unrestricted allowance trading is preferable over restricted allowance trading not only for the EU but also for China. Still, the authors conclude that restricted allowance trading should be sought after in the mid-term, as such restriction can reduce the negative side effects of full linking, which are not depicted in welfare: the decelerated development of EU's renewable energy production (stemming from the opportunity to buy allowances from China rather than mitigating domestic emissions) and the reduced international competitiveness of China's energy intensive sectors (stemming from higher carbon prices in a fully linked ETS). Such argument in favour of restricted allowance trading gains additional weight against the background of the findings from our study, in which China benefits more under half linking compared to full linking.

We are not aware of any other study analysing the effects of linking the EU and the Chinese ETS for a disaggregated EU. Therefore, our results provide new insights into whether linking benefiting the EU as a whole will also benefit its member states. The results reveal that unanimous gain in all the EU sub-regions is not systematic and depends on factors such as the degree of linking, choice of mechanism, and the emission target to be met. Overall, all the EU regions experience welfare gains only in the "restricted trading" scenarios, when trading of more than 60% of allowances occurs. Thus, for strengthening the case in support for linking and consequently increasing the likelihood of political acceptance for linking the EU ETS to the Chinese ETS, the creation of

⁵¹ Trading is restricted to one-third of the EU's reduction (against 2005 emissions) in each year in Hübner et al. 2014.

transfer mechanisms within the EU is essential.

In this study, we focus on the gains associated with linking under NDCs and model these as absolute reduction targets both for the EU and China, in line with the overall EMF36 round (Böhringer et al., 2021). However, China's ETS integrates an intensity target (see International Energy Agency (IEA)). This implies the possibility for different absolute CO₂ emissions (see e.g. Liu and Wei 2016) and, thus, different results also for carbon prices and, thus, incentives to link. Hübler et al. (2014) implement scenarios with different assumptions regarding China's economic growth. This is relevant not only with regard to the intensity target, but also concerning the current situation, in which the world faces unforeseeable consequences of the COVID-19 crisis, international trade dispute, and possible de-globalization. However, the overall trends and findings we derive here are not likely to be qualitatively affected by our absolute reduction approach. Another dimension not covered in our study is the interaction of ETS with other climate or energy policies. Liu and Wei (2016) model a combination of linking EU and Chinese ETS plus introducing renewable subsidies and find important interactions between the two policies. Furthermore, we do not include transaction costs or political barriers that might hinder the linking of ETS. While this aspect is beyond the scope of our CGE study, one should keep in mind that these barriers can seriously hamper or even prevent the linking of ETS, be it economically feasible or not (see e.g. Hawkins and Jegou 2014, Flachsland et al. 2009). All these aspects could be subject to future studies on the feasibility and effects of linking the EU and China's ETS.

6.5 Conclusions

In this study we analyse the assumptions under which linking between an EU ETS and a Chinese ETS in the energy intensive sectors and the power sector is beneficial for each of the trading partners. Furthermore, we disaggregate the EU and analyse our modelling results also at the sub-EU level. We find that restricted allowance trading is more beneficial to China than full allowance trading, and China's welfare is maximized when the traded volume of allowances is restricted to 50% of the volume traded in a fully linked system. For the EU, full allowance trading is always more beneficial than restricted allowance trading. Another option to make the linking of ETS more attractive to China would be to transfer payments from the EU to China. The EU could favour this option in combination with a full link over a situation with restricted allowance trading but no

transfer payments. For China, the opposite is true: restricted trading is favoured over transfer payments.

While changes in international trade (modelled in our “Armington elasticities” scenarios) affect China more strongly than the EU, linking of ETS would become more attractive for China with less open trade, especially if trade barriers aim at ETS sectors: Here, trading of emission allowances could offset the loss originating from decreasing trade of goods. Generally, all trading partners benefit from more trade-openness and linking ETS further increases these benefits.

In addition to the different options favoured by the EU on the one hand and China on the other hand, there are also competing interests among the single EU regions in several scenarios. Namely, regions which are net allowance sellers in a separate EU ETS (not linked to the Chinese ETS) face potential losses when the cheaper Chinese allowances enter the European allowances market. Consequently, even though the linking of EU and Chinese ETS is beneficial to both the EU and China in all our scenarios except one, designing options which can be agreed upon by all trading partners will be difficult, both inside the EU and between the EU and China. This holds especially true when political feasibility is also considered. The possible outcomes of hypothetical negotiations on designing a joint EU–Chinese ETS from a political economy standpoint should be evaluated in future studies.

6.6 Appendix

Non-technical description of the DART Kiel model

The DART Kiel model is a multi-region, multi-sector, recursive dynamic CGE model. The version used in this study is based on the GTAP 9 data base for 2011 (Aguiar et al. 2016) and the related GTAP-9 Power data base (Peters 2016) and contains the following sectors and regions.

Table 6.6A: DART Kiel regions

Europe	
GBR	United Kingdom, Ireland
SCA	Denmark, Finland, Sweden, Norway
DEU	Germany
FRA	France
BLX	Benelux
SEU	Southern Europe: Austria, Italy, Spain, Portugal, Malta, Greece, Cyprus
EEU	Czech Republic, Slovakia, Slovenia, Hungary, Estonia, Latvia, Lithuania, Bulgaria, Romania, Croatia, Poland
REU	Rest EU incl. Iceland, Liechtenstein, Switzerland, Albania, Belarus, Ukraine,
Americas	
CAN	Canada
USA	USA
BRA	Brazil
OAM	Other Americas
Russia & Asia & Pacific	
RUS	Russia
IND	India
ANZ	Australia, New Zealand
JPN	Japan
CPA	China, Kong-Kong
KOR	Korea
OAS	Other Asia
Africa & middle East	
MEA	Middle East
AFR	Africa

Table 6.7A: DART Kiel sectors

Energy & Electricity		Other	
Col	Coal	EIT	Energy Intensive Sectors
Cru	Crude oil	TRN	Transport Aggregate
Gas	Natural gas	AGR	Agriculture & Food
Oil	Refined oil products	MFR	Other manufactured goods
ENuclear,	Electricity from Nuclear	SER	Services

ECoal	Electricity from Coal	CGD	Savings good / Aggregate Investment
EGas	Electricity from Gas		
EWind	Electricity from Wind		
EHydro	Electricity from Hydro		
EOil	Electricity from Oil		
ESolar	Electricity from Solar,		
EOther	Electricity from Other		

The economic structure for each region covers production, consumption, investment and governmental activity. Markets are perfectly competitive. Prices are fully flexible. For each region, the model incorporates three types of agents: the producers, distinguished by production sectors, the representative private household and the government.

Producer Behavior

All industry sectors are assumed to operate at constant returns to scale. Output of each production sector is produced by the combination of energy, non-energy intermediate inputs, and the primary factors labour and capital (land in the agricultural sector). Figure 6.6A and Figure 6.7A show the nested production structure for non-energy goods and fossil energy.

Figure 6.6A: Nesting of non-energy production

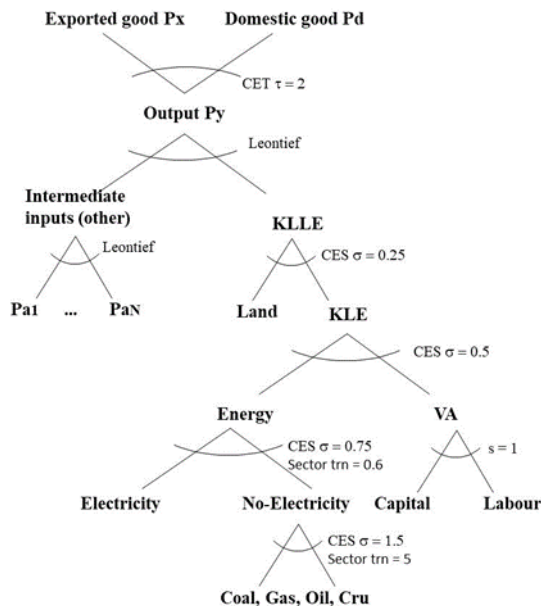
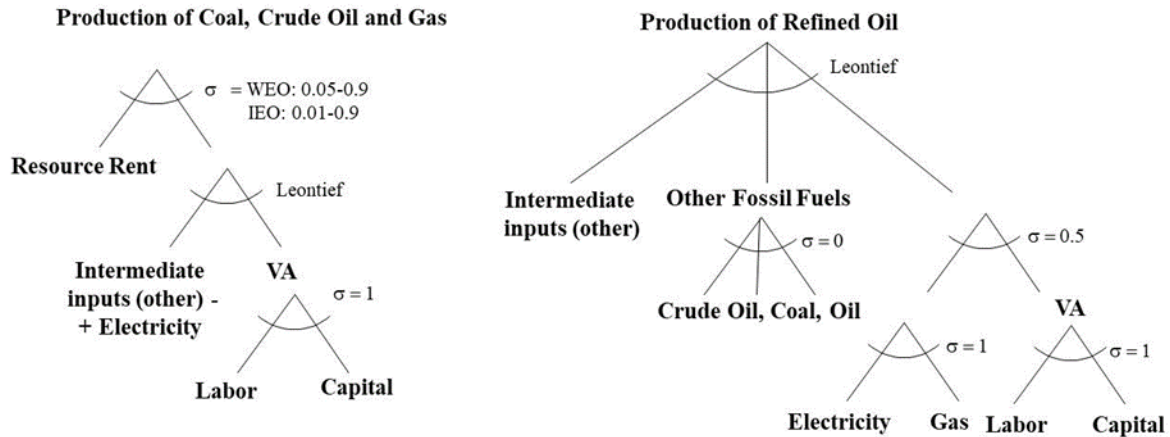
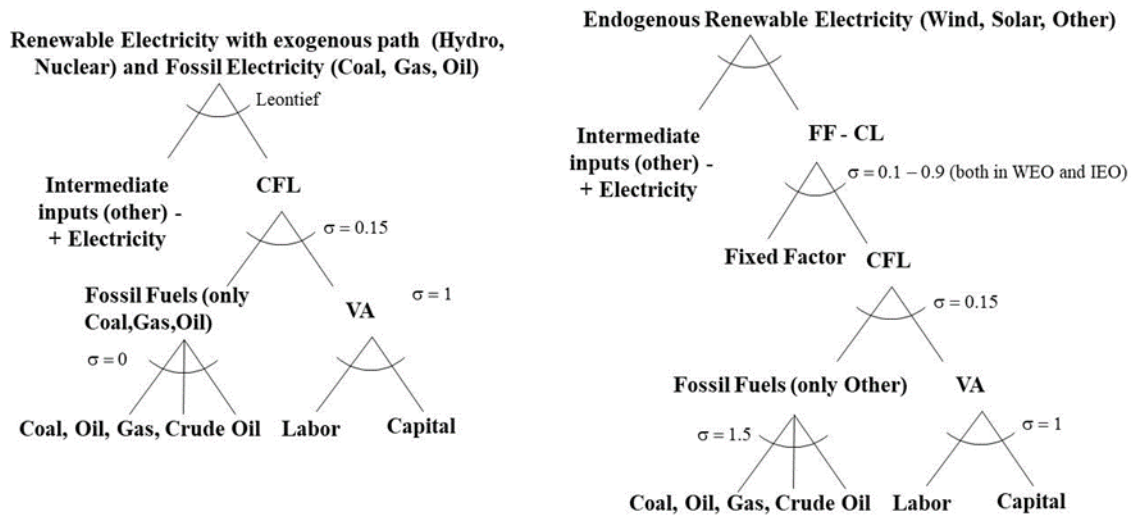


Figure 6.7A: Nesting of fossil fuel production



Electricity production is differentiated between coal, gas, oil, hydro, nuclear, wind and solar based electricity plus other electricity. The elasticity of substitution between the different types of electricity is 12. Note that we do not use the baseload-peak load disaggregation proposed in Peters (2016), but aggregate e.g. GasBL and GasP to EGas. The nesting structure is depicted in Figure 6.8A.

Figure 6.8A: Nesting of electricity production



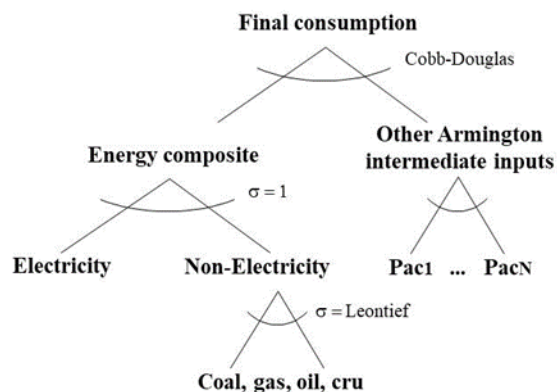
Composite investment is a Leontief aggregation of Armington inputs by each industry sector. Investment does not require direct primary factor inputs. Producer goods are directly demanded by regional households, governments, investment sector, other industries, and the export sector.

Consumption and Government Expenditure

The representative household receives all income generated by providing primary factors to the production process. Disposable income is used for maximizing utility by purchasing goods after taxes and savings are deducted. Private consumption is calibrated to a LES, which divides demand into subsistence and supernumerary consumption based on a Stone-Geary utility function. Households first spend a fixed part of their income on a subsistence quantity for each commodity and allocate their supernumerary income to different commodities according to fixed marginal budget shares which are the product of average budget shares and income elasticities of demand. This division of total consumption into fixed subsistence and flexible supernumerary quantities allows for a calibration to non-unitary income elasticities and non-homothetic preferences. To avoid that, the LES will eventually converge to a Cobb-Douglas system and approach homothetic preferences when income grows, the subsistence quantities are updated with population growth in each period following Schünemann and Delzeit 2019⁵², which also includes further information on the LES calibration.

The third agent, the government, provides a public good which is produced with commodities purchased at market prices. Public goods are produced with the same two-level nesting structure as the household “production” function (see Figure 6.9A). The public good is financed by tax revenues.

Figure 6.9A: Nesting structure of final consumption



52 Schünemann, F., Delzeit, R. (2019). Higher Income and Higher Prices: The Role of Demand Specifications and Elasticities of Livestock Products for Global Land Use. *Schriften der Gesellschaft für Wirtschafts- und Sozialwissenschaften des Landbaues e.V.*, Bd. 64, 185-207.

Foreign trade

The world is divided into economic regions, which are linked by bilateral trade flows. All goods are traded among regions, except for the investment good. Following the proposition of Armington (1969), domestic and foreign goods are imperfect substitutes, and distinguished by country of origin. Transport costs, distinguished by commodity and bilateral flow, apply to international trade but not to domestic sales.

On the export side, the Armington assumption applies to final output of the industry sectors destined for domestic and international markets. Here, produced commodities for the domestic and for the international market are no perfect substitutes. Exports are not differentiated by country of destination.

Factor markets

Factor markets are perfectly competitive and full employment of all factors is assumed. Labor is assumed to be a homogenous goods, mobile across industries within regions but internationally immobile. The capital stock is given at the beginning of each time period and results from the capital accumulation equation. Capital is also region specific and a putty-lay vintage capital approach is chosen, so that only new investment is mobile across sectors. In every time period the regional capital stock earns a correspondent amount of income measured as physical units in terms of capital services. The primary factor land is only used in agricultural sectors and exogenously given.

Coverage of GHG emissions

DART covers CO₂-emissions from the burning of fossil fuels taken from the GTAP 9 data base.

Dynamics and Calibration

The DART Kiel model is recursive-dynamic, meaning that it solves for a sequence of static one-period equilibria for future time periods connected through capital accumulation. The major driving exogenous factors of the model dynamics are change in the labour force, the savings rate, the depreciation rate and the gross rate of return on capital, and thus the endogenous rate of capital accumulation. Finally, the rate of total factor productivity (TFP) growth is used to calibrate DART Kiel to a given GDP-path. For the EMF-36 GDP baseline it was in addition necessary to reduce

the growth of the labour force for a few regions since already a TFP of zero led to too high growth rates. If this was still not enough also depreciation was increased.

Finally, it turned out that the given Chinese GDP value for 2030 could not be reached with higher TFP in China alone but required import let growth in DART. For this reason, the usual Armington elasticities we increased by 1.5 worldwide. Table 6.8A below shows the base data and these adjustments.

The savings behaviour of regional households is characterized by a constant savings rate over time. This rate is allowed to adjust to income changes in regions with extraordinary high benchmark savings rates, namely China, India, AFR, OAS and KOR. Labour supply considers population growth and the development of the share of the working force in the population.

The supply of the sector-specific factor land is held fixed to its benchmark level over time. Current period's investment augments the capital stock in the next period. The allocation of new capital among sectors follows from the intra-period optimization of the firms.

Furthermore, the baseline path of renewable electricity plus nuclear is calibrated to match the projections of the IEA. The development of electricity from hydro and nuclear is fixed at an exogenous growth path through an endogenous subsidy. For solar- and wind-power as well as other-electricity, we adjust the growth of the fixed factor and the elasticity of substitution between the fixed factor and the other inputs to calibrate to the given path that then also reacts to policy shocks.

Emissions are traditionally calibrated only on global level for CO₂-emissions from gas, coal and oil by adjusting the supply elasticity of these fossil fuels. To achieve a given regional emission level at 2030 for the EMf-36 scenarios we used regional supply elasticities of fossil fuels and in addition adjusted the autonomous energy efficiency improvement (AEEI) which is typically 1% p.a. to achieve the required emission intensity of GDP. In India even very high rates were not sufficient to bring down emission intensity sufficiently so we increased the KLE elasticity as well. Finally, the WEO baseline used in this study is based on carbon prices for the EITE sector and the power sector in Europe (27\$/tCO₂) China (20\$/tCO₂), Canada (36.5\$/tCO₂) and Korea (28\$/tCO₂)⁵³. We also implemented carbon prices for WEO in EITE sectors starting in 2015 and

⁵³ The values in brackets are extrapolated from the 2025 and 2040 values given by WEO.

linearly rising to the given level in 2030. To match the given CO₂ level in 2030 and for the EU the communicated targets for the EU emissions trading scheme, the prices were slightly adjusted to 21\$/tCO₂ in Europe, 18 \$/tCO₂ in Canada, 15 \$/tCO₂ in China and 14 \$/tCO₂ in Korea.

Relevant elasticities and parameter are summarized in Table 6.8A. We use the same method as Böhringer et al. (2021) to calibrate the emissions from ETS and non-ETS sectors in the EU for our Baseline. As a result, in our Baseline the total CO₂ emissions in EU ETS sectors increase by 20.6%, while in the non-ETS sectors they reduce by 0.6%, which results in an overall increase of 4.4% in emissions, all relative to Baseline.

Table 6.8A: Core parameters and adjustments for EMF calibration

Parameters	Explanation	Value	Adjustment for EMF - WEO Baseline
ESUB_ES(*,r)	Elasticity fixed resource with KLE in coal, gas, cru production	Default: Coal 0.3, GAS 0.2, CRU 0.2	0 to 0.8 to calibrate regional emission path
ESUB_ELE(I)	Substitution elasticity between electricity vs non-electric energy	Transport 6, Rest sectors 0.75	
ESUB_NE(I)	Substitution elasticity between non-electric energy types	Transport 5, Rest sectors 1.5	
ESUB_LD(r)	land vs KLE	0.25	
ESUB_KLE(r,i)	Energy vs KL	0.5	IND: 0.75; BRA: 0.85
S	Substitution elasticity between KLE vs material	0	
ESUB_ELE	Substitution elasticity between different electricity types	12	
VA	Substitution elasticity between K vs L	1	
ESUB_RES(*,r)	Elasticity of fixed resource EWind, ESolar, EOther	Default: 0.1	0 to 0.8 to calibrate path
PRELEEXP(*,r)	Exponent for increase of fixed factor EWind, ESolar, EOther		0 to 0.9 to calibrate path
ARMEL(i,r)	Substitution elasticity between imports from different regions	GTAP database All electricity types 2.8, COL 3.05, CRU	min(12,1.5*armel(i,r)); All electricity types 4.2, COL 4.6, CRU 12, GAS

		12.849, GAS 12.849, OIL 2.1, EIT 3.239, TRN 1.9, AGR 2.761, MFR 3.529, SER 1.917	12, OIL 3.2, EIT 4.9, TRN 2.9, AGR 4.1, MFR 5.3, SER 2.9
ARM_REG(I)	Substitution elasticity between imports vs domestic goods	Min (14, 2*ARMEL)	Min(14,1.5*arm_reg(i);
AEEI(r)	Autonomous Energy Efficiency Improvement p.a.	1% p.a. in all regions	AFR 1%; BLX 2.5%; BRA 0%; CAN 0.5%; CHN 2.4%; EEU 1.3%; FRA 2.5%; GBR 1.5%; GER 0.7%; IND 2.8%; MEA 2.4%; OAM 1.5%; REU 2%; RUS 0.3%; SCA 2.3%; SEU 0.4%; USA 2.1%; OAS 1.8%; JPN 1.7%; KOR 0.6%; ANZ 0.8%
DEP(r)	Depreciation rate of capital p.a.	0.04	OAM: 0.045; MEA: 0.045
FFSHARE(*,r)	Fixed factor shares in ESolar and EWind	0.1	
SUB	Substitution elasticity between energy composite and other inputs for final demand	1	
WRKAD(r)	Adjustment factor in growth of labour force	1	MEA: 0.8; OAM: 0.8; CHN: 0

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7 Interaction between the European Emission Trading System and renewable electricity⁵⁴

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ABSTRACT

Changes in the allowance price in the EU emissions trading system (EU-ETS) may cause several side effects: shifts in energy portfolios and inter-sectoral carbon leakage, shifts in inner-European burden sharing of greenhouse gas (GHG) abatement and international carbon leakage. We use the global computable general equilibrium model DART to quantitatively analyse the effects of increased allowance price, technological growth in renewables, flexibility in electricity consumption and technology substitution. Our results show that the allowance price and the share of renewables are the decisive factors for the EU-regions share in GHG abatement. High allowance prices reduce the production of coal based-electricity, thus increasing the share of GHG abatement in EU regions with a large share of coal in their electricity portfolio. Inter-sectoral carbon leakage is highest when households can easily substitute electricity with fossil fuels. It is lowest when sectors outside the EU-ETS are targeted with climate mitigation policies but at the cost of higher EU-ETS prices and international leakage. We identify the decreasing prices for coal as the main channel for international carbon leakage, which increases coal-based electricity production outside the EU. Even though the EU-ETS does not directly target renewables, technological improvements in this sector can substantially decrease the allowance price and therefore help mitigate inter-sectoral and international leakage effects of the EU-ETS.

Keywords: EU-ETS, allowance price, carbon leakage, renewable energies, CGE, energy policy

⁵⁴ This chapter is currently under review in Climate Policy. An older version of this paper is was published online under the GTAP Conference Proceedings in 2019. Retrievable under: https://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=5785

7.1 Introduction

Electricity production plays a central role in the EU's climate policy and in 2016, it accounted for one-third of the European Union's (EU) CO₂ emissions (IEA 2018). The EU follows a two-fold approach to decrease these sectoral emissions: first, by fostering the uptake of renewable energy technologies and second, by pricing CO₂ emissions from fossil-based electricity production via the European Emission Trading System (EU-ETS). In this paper, we examine the interconnection of the two approaches and explore how supporting growth of renewables could interact with the EU-ETS.

Numerous instruments both in the EU and its member states target several aspects related to the strengthening of renewable energies in the electricity portfolio. For example, the EU's Innovation and Modernization Funds⁵⁵, which are financed by revenues from auctioning off the EU-ETS allowances, aim to develop low greenhouse gas (GHG) technologies and improve energy efficiency. While this is a promising approach, there are growing concerns that technological barriers could hinder the integration of renewables on a larger scale due to the incapability of electricity grids in handling the volatile production typical for wind and solar technologies.

The EU Emissions Trading System (EU-ETS) is the central instrument of the EU (Böhringer and Lange 2012; ICAP 2016) to reduce CO₂ emissions from fossil electricity production. The current EU-ETS regulates the GHG emissions of large energy producing facilities (greater than 20 MW), energy-intensive industries (with sector-specific size limits), and inner-European air traffic. In total, roughly one half (~40%) of the total European GHG emissions are covered by the EU-ETS (ICAP 2016; EC 2015)⁵⁶.

Even though not targeted by the same policy instruments, renewables and fossil-based electricity are closely related, as they produce almost homogenous goods (depending on the flexibility of the electricity net). By increasing the production cost of fossil fuels via the EU-ETS and increasing the learning curve and subsidies of renewables, both policies increase the competitiveness of renewables compared to fossil electricity. Consequently, the share of renewables in electricity

⁵⁵ For further details about EU's Innovation and Modernization Funds, please refer to https://ec.europa.eu/clima/policies/innovation-fund_en and https://ec.europa.eu/clima/policies/budget/modernisation-fund_en, respectively.

⁵⁶ In addition to CO₂ emissions from fossil fuels, the EU-ETS also targets emissions of nitrous oxide (N₂O) from production of nitric, adipic and glyoxylic acids and glyoxal and perfluorocarbons (PFCs) from aluminum production.

generation increased from 14% (431 TWh) in 2000 to 30% (977 TWh) in 2016. At the same time the share of CO₂ emissions from the power sector decreased from 37% (1378 MtCO₂) in 2000 to 34% (1077 MtCO₂) in 2016 (IEA 2018).

However, the two-fold approach comes with some potential pitfalls if the overlapping policies are not well designed. Böhringer and Rosendahl (2010) show that the introduction of quotas for green technologies in the presence of tradeable quotas for fossil technologies could counter-intuitively lead to increased production of the most carbon-intensive fossil technology. Abrell and Weigt (2008) examine the interaction of the EU-ETS and renewable supporting policies in Germany and show that renewable support policies lead to lower carbon prices and that the implementation of a renewable quota in addition to an ETS leads to welfare losses. Liu and Wei (2016) find that lower allowance prices hinder growth in renewable energy production in the EU. Del Rio González (2007) highlight the possibility to foster synergies between ETS and support schemes for renewables by coordinating both instruments' targets.

For the evaluation of the economic and environmental effects of EU climate policies, one needs to examine the emission balance beyond electricity production, since carbon leakage might occur when some goods are burdened with a price on emissions (like sectors, facilities or regions inside an ETS), and others are not (like sectors, facilities or regions outside an ETS). The literature highlights two main channels of carbon leakage (Tan et al. 2018): direct competitiveness effects caused by a change in relative prices of goods and indirect competitiveness effects caused by a change in international fossil fuel prices. Both effects can have both an international and a domestic dimension.

Direct competitiveness effects occur when only some goods targeted with a GHG price, making them relatively more expensive. This price change impacts consumption decisions and leads to substitution towards other goods with no-GHG price or the same good produced in a region with no GHG price. This change in consumption decisions could lead to (over-)compensation of GHG abatements in targeted regions or sectors (see e. g. Babiker 2005). To our best knowledge, this is the first study that uses an ex-ante modelling approach to quantify carbon leakage caused by changes in consumption decisions within the EU.

In the international dimension, carbon leakage typically refers to the displacement of sectoral production of a good from a region with a GHG price to a region without a GHG price. This effect has widely been discussed in the literature (e. g. Carbone and Rivers 2017; Branger and Quirion 2014; Martin et al. 2016; Verde 2018; Bernard and Vielle 2009) with regard to competitive disadvantages of firms or sectors facing a price on emissions relative to counterpart firms or sectors in regions without a price on emissions. However, the conclusions from studies depend on modelling assumptions (Carbone and Rivers 2017).

Evidence of carbon leakage in the range of 5-20% is seen in ex-ante studies but not in empirical ex-post econometric studies (Branger and Quirion 2014). Ex-ante studies specific to the EU-ETS only find low leakage rates (Bernard and Vielle 2009; Barker et al. 2007). Other studies also show that no traceable international carbon leakage has been observed (reviews by Verde, 2018 and Martin et al.,2016). This result is mainly attributed to the low EU-ETS allowance price in the period when studies were conducted, along with the practice of the free distribution of allowances to avoid competitive disadvantages to European industries (Demailly and Quirion 2006; Naegele and Zaklan 2019; Joltreau and Sommerfeld 2018). Other studies (Barker et al. 2007; Gerlagh and Kuik 2014) show that if technology spillovers are considered, the EU could also experience negative carbon leakage.

The second channel of carbon leakage causes indirect competitiveness effects through changes in international prices of fossil fuels. Emission pricing and falling production cost of renewables leads to a decrease in fossil-based electricity production. This lowers the demand for fossil fuels and, thus, a drop in the international price of fossil fuels. Such a price drop could increase the demand for fossil fuels in sectors or regions that are outside the carbon pricing regime (Böhringer et al. 2010) and causing carbon leakage.

This paper addresses the interplay between EU-ETS allowance prices and supporting policies for renewable energies. It analyses the effects on different channels and dimensions of carbon leakage in order to evaluate the effectiveness of the two main pillars of EU climate policies. We use a global, static general equilibrium model with a detailed representation of electricity producing technologies for our analysis. We develop three policy scenarios that characterize increased learning of renewables, limited net integration of renewables, and easier technology adaption for

private consumers in our analysis. We analyse both inter-sectoral and international carbon leakage effects.

The rest of the paper is structured as follows: Section 7.2 contains a description of the model version used in this study and Section 7.3 described the implemented scenarios. Modelling results are described in section 7.4. Finally, section 7.5 provides a discussion and concludes.

7.2 Model description

DART is a global multi-sectoral, multi-regional recursive-dynamic CGE model. In this study, we use a static version of DART. Developed at the Kiel Institute for the World Economy, it has been widely applied to analyse international climate policies, (e.g. Klepper and Peterson 2006a, Springer 2002, Springer 1998), environmental policies (Klepper and Peterson 2006b), energy policies (e.g. Weitzel et al. 2012), and agricultural and biofuel policies (e.g., Calzadilla et al. 2016; Delzeit et al. 2018). In DART, the global economy is represented by 20 regions and 19 sectors (see Table 7.1). Regional markets are assumed to be competitive. Prices are flexible and all markets clear in equilibrium.

Table 7.1: Regions and sectors in DART. * indicates the EU-ETS regions and sectors.

Region	Description	Region	Description
FRA *	France	USA	USA
GER *	Germany	CAN	Canada
ITA *	Italy	PAS	Pacific Asia
GBR *	United Kingdom, Ireland	RUS	Russia
BLX *	Belgium, Netherlands, Luxembourg	FSU	Former Soviet Union (excluding Russia)
SPO *	Spain, Portugal	CPA	China, Hong Kong
SCA *	Denmark, Finland, Sweden, Norway	IND	India
EHC*	Europe high carbon ⁵⁷	LAM	Latin America
ELC*	Europe low carbon ⁵⁸	RAXB	Japan, Australia, New Zealand and Switzerland
AFR	Sub-Saharan Africa	MEA	Middle East, Northern Africa, Turkey

⁵⁷ Includes countries with more than 20% of coal in the energy sector based on Eurostat (Poland, Czech Republic, Bulgaria, Greece, Slovenia)

⁵⁸ Includes countries with less than 20% of coal in the energy sector based on Eurostat (Romania, Hungary, Slovakia, Baltic States, Cyprus, Malta, Croatia Austria, Liechtenstein, Iceland)

Energy sectors	Description	Non-energy sectors	Description
ECoal*	Coal based electricity	ESolar	Solar based electricity
EGas*	Gas based electricity	EWind	Wind based electricity
EOil*	Oil based electricity	ENuclear	Nuclear based electricity
PPP*	Pulp, paper and print	AGR	Agriculture (no livestock) & forestry
CRP*	Chemical Rubber Products	CTL	Livestock
M_M*	Production of metals and minerals	OTP	Commercial road and rail transport ⁵⁹
EOther*	Electricity from biomass, waste, geothermal, tides	FFP	Fossil fuel production (coal, natural gas, crude oil)
OIL*	Oil Refining to produce oil products	WATP	Commercial water and air transport
EHydro	Hydro based electricity	O_I	Other industry
		SVCS	Services

Production from each sector is defined using a nested Constant Elasticity of Substitution (CES) function. The nesting structures are available upon request. The economic structures in DART are fully specified for each region and covers production, investment and final consumption by private consumers and the government (Calzadilla et al. 2016). Consumer demand is modelled with non-unitary income elasticities using the linear expenditure system (LES) approach (Stone 1954).

DART is based on the GTAP9 Power database (Aguilar et al. 2016; Peters 2016), representing the global economy in 2011. Electricity⁶⁰ is produced from renewable (wind, solar, others (incl. biofuels, waste, geothermal, and tidal technologies)), conventional (coal, gas, oil), and nuclear technologies and finally aggregated as a homogenous commodity. We aggregate the baseload and peak load sectors from the original GTAP9 Power database into a single sector. Solar and wind technologies are modelled with a learning curve model using the fixed resource approach (Paltsev et al., 2005) to have a stable production pathway. The fixed resource is a share of the sectoral capital and is set to 10%. We assume that electricity produced from nuclear and hydro technologies are policy-driven rather than market-driven and are therefore stable over time.

A technical description of the implementation of fixed factor in DART is provided in Weitzel

⁵⁹ Note that private road transport is not part of sector OTP, but is included into the model via direct household consumption of fossil fuels. The same accounts to private heating.

⁶⁰ We use the term “electricity” while we are aware that the sectors of the GTAP-Power sector include also part of sectoral heat production.

(2010). Our model has a detailed accounting of both CO₂ and non-CO₂ emissions based on the GTAP database. The CO₂ emissions account for the emissions produced from fossil fuel combustion and the non-CO₂ emissions cover emissions from methane, nitrous oxide and fluorinated gases.

The EU-ETS is implemented into DART on the regions and sectors marked with a ‘*’ in Table 7.1. The allowance price is modelled by imposing a price on CO₂ emissions from fossil fuel combustion in the EU-ETS sectors. The allowance price is determined by restricting the amount of emissions allowed in the participating regions and sectors and this “endowment” of emissions can be interpreted as the EU wide emission cap.

7.3 Description of scenarios

We model one baseline and five policy scenarios as shown in Table 7.2. In order to account for the large increase of the share of renewables between 2011 and 2015 in the European countries, the **Baseline** is calibrated to meet the European energy portfolios of 2015 based on the shares provided in IEA (2018). The calibrated progress rates for wind and solar are 0.42 and 0.41, respectively. Nuclear and hydro electricity technologies are calibrated to their levels in 2015 and remain fixed throughout all policy scenarios. The EU-ETS cap is chosen in order to meet the average 2015 price of 6 €/tCO₂, and no GHG reduction targets are assumed for the sectors outside the EU-ETS.

Among the policy scenarios, **ET100** represents a policy that enforces a stricter GHG emissions reduction target (cap) within the EU-ETS. In the rest of the policy scenarios we keep the same GHG emissions reduction cap for the EU-ETS. Unless stated otherwise (see Table 7.2), the other four policy scenarios carry the same parameter values as in ET100. **DoubleLearn** represents a policy with steeper learning curves of wind and solar, **FlexCons** represents more flexible adaptation between types of fossil fuel consumed by private consumers in final demand and **SecRed** simulates GHG mitigation policies for non-EU-ETS sectors by imposing a cap on these sectors’ GHG emissions. To test the sensitivity of our results, we simulate scenario **Eesub7** with reduced flexibility in integration of renewables into the electricity grid. In our scenarios we assume that only the EU implements additional climate policies while the rest of the world remains on a business-as-usual pathway with no further climate policies.

Table 7.2: Description of scenarios

Scenario	Description	Policy significance
<i>Baseline</i>	Baseline scenario	
<i>ET100</i>	EU-ETS price is calibrated to 100€/tCO ₂ via a reduction of allowances	Reduction of the EU-ETS Cap
<i>DoubleLearn</i>	Doubled learning rates for wind and solar technologies	Technological advancement in solar and wind electricity
<i>FlexCons</i>	Increased flexibility of substitution between electricity sectors and all non-electric fossil fuel sectors for private and public consumers by increasing elasticity of substitution in the demand function from Cobb-Douglas to 2.	Consumer preferences flexibly adapt to changing energy prices. For e.g. substituting fossil based private transport by an electric capturing the shift to electric mobility
<i>SecRed</i>	Sectoral emission reduction targets for EU non-ETS sectors based on the reported reductions in 2011-2015 (UNFCCC 2017)	Effort Sharing Agreement implemented
<i>Eesub7</i>	Elasticity of substitution between different electricity technologies is halved	Hindrance in grid-integration of renewable electricity

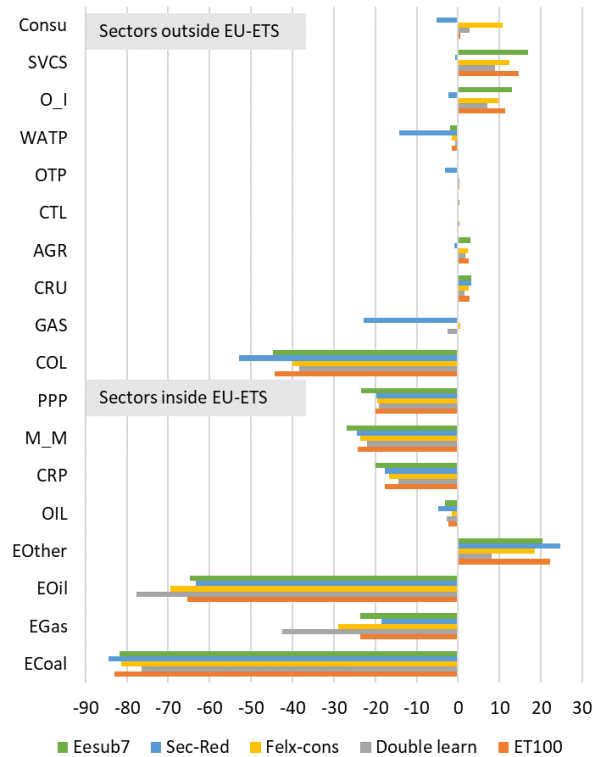
7.4 Results

7.4.1 Effects on allowance price and GHG emissions in the EU

The introduction of a strict cap in scenario *ET100* substantially decreases the GHG emissions of the sectors within the EU-ETS (see Figure 7.1). In general, there are two ways by which emissions can be reduced domestically: either by a reduction in overall production or by input substitution (away from emission-intensive fuels and towards non-energy inputs).

In all scenarios, the highest absolute emission reductions occur in the EU-ETS electricity sectors, namely power generation based on coal, gas, and oil. In fossil-based electricity technologies, emission levels are directly linked to production levels. Coal has the highest implied emission factor in the fossil fuels. Therefore, among the electricity generating sectors, the increase in production cost is highest for coal-based electricity with higher prices in the EU-ETS and thus are emission reductions observed in coal-based electricity production (ECoal) throughout all scenarios (Figure 7.1).

Figure 7.1: Percentage changes in sectoral GHG emissions compared to Baseline for the whole EU



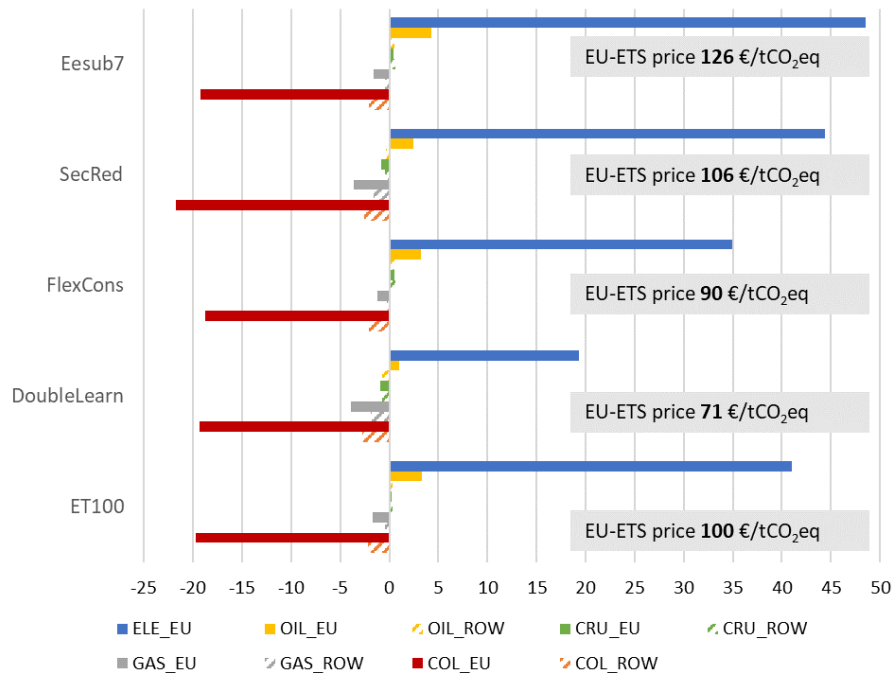
When looking at individual EU regions, all except BLX and EHC reduce emissions from ECoal by at least 88% when the strict cap is introduced in *ET100*. Consequently, countries with the highest share of coal in the electricity portfolio exhibit the highest GHG reductions (compared to *Baseline*) (see Table 7.3A for countries' share of Ecoal and GHG reduction). The share of ECoal is largest in Germany with 44% ECoal and 28% GHG reductions, followed by EHC with 64% ECoal and 20% GHG reductions. On the other hand, France, with only 2% ECoal in electricity production, exhibits only a 5% reduction in GHG emissions in the *ET100* scenario.

When the allowance price changes in the other scenarios, emission reductions in the electricity sectors in the EU-ETS adjust accordingly. For example, double learning in renewables leads to a lower price for emission allowances of 71€/tCO₂ (see first line of Table 7.4A), and consequently to lower emission reduction of ECoal (by almost 8 percentage points) in the EU compared to *ET100*.

Even though they face the same change in emission allowance price, in contrast to ECoal, EGas (80%) and EOil (19%) have higher emission reductions in *DoubleLearn* compared to *ET100*

(though still on a much lower level than emission reductions of ECoal in absolute terms). With coal having the highest emission factor, decreases in production costs of ECoal are relatively higher compared to EGas and EOil with a lower price in the EU-ETS. Consequently, in *DoubleLearn*, ECoal exhibits higher levels of production than in *ET100* since it increases its relative competitiveness. This overall effect for the EU is dominated by the EU countries with low shares of renewables (see Table 7.4A) since in these countries results are driven by the lower price for allowances because the decrease in the production cost of renewables due to steeper learning curves in *DoubleLearn* has less impact. For example, in *Baseline*, EHC with a share of renewables of only 12%, increases its total emissions (3% compared to *ET100*), driven by emissions from ECoal. In contrast, Germany has a high share of ECoal (44%) and a relatively high share of renewables (23%) in *Baseline*. The share of renewables increases in *DoubleLearn* (to 53%; 43% in *ET100*), and therefore Germany decreases its CO₂-emissions from ECoal by 46% compared to *ET100*.

Figure 7.2: EUETS allowance price and percentage changes in input prices of fossil fuels and electricity in the EU and rest of the world (ROW)



We observe the same effect in *FlexCons*, even though on a smaller level. The opposite effect occurs in *SecRed*, where allowance prices are higher than in *ET100* (106€/tCO₂eq, see Table 7.4A). More emissions are reduced from ECoal compared to *ET100*, and slightly less from EGas and EOil. The

higher allowance price increases the relative contribution of ECoal to total emission reductions but decreases that of EGas and EOil. Thus, policy settings outside the EU-ETS (e.g. better promotion of renewables or higher consumer flexibility) affect the contribution of each power generation technology to emission mitigation inside the EU-ETS via the allowance price.

Among the non-energy sectors in the EU-ETS, mineral and metal production (M_M) as well as the chemical sector (CRP) show the highest reduction in emissions, followed by pulp, paper and print (PPP). The emission reduction pattern of these three sectors follows the EU-ETS emission allowances price: The lowest reduction occurs in *DoubleLearn* (where the allowance price is lowest with 70€/tCO₂eq), the highest in *Eesub7* (where the allowance price is highest with 126€/tCO₂eq). In *Baseline*, these three sectors use small amounts of coal and more oil and gas. When the ETS cap is strengthened in *ET100*, all three sectors reduce their gas consumption (CRP: 26%; M_M: 29%; PPP: 18%), and coal is hardly used anymore. Interestingly, we observe an increase in the consumption of oil (CRP: 7%; M_M: 13%; PPP: 23%), which in energy terms (mtoe) slightly overcompensates the reduction in coal and gas use. Thus, within these sectors, we observe a substitution effect towards oil, which, due to the lower emission factors for oil in the GTAP database compared to coal, reduces the emission of the sectors without decreasing the overall use of fossil fuels. This effect is less pronounced in *DoubleLearn* and the strongest in *SecRed* and *Eesub7*, where the higher prices for emission allowances increase the relative price differences between the different fossil fuels.

7.4.2 Inter-sectoral Leakage Effects outside the EU-ETS

While tightening the ETS cap in *ET100* (compared to *Baseline*) does not directly address the non-ETS, we still observe an increase in GHG emissions in these sectors (see Figure 7.1), which indicates inter-sectoral leakage resulting from higher allowance prices. When comparing *ET100* to *Baseline*, the percentage leakage⁶¹ amounts to 9.4%, meaning that 9.4% of the emissions abated within the EU-ETS are offset by additional emissions in non-ETS sectors. These are largest in the service sector, both in relative (15%) and absolute (64 tCO₂eq) terms. The increase in emissions is larger than the emission reduction of EGas (56 tCO₂eq) and EOil (54 tCO₂eq) in the EU-ETS.

⁶¹ We use the concept of percentage leakage, which is defined in (Metz et al. 2007) as the percentage of the increased CO₂ emissions in non-EU regions relative to the emissions abated in the EU-ETS, and apply it also to CO₂ emissions in non-ETS sectors relative to abatements in ETS sectors.

The sector “Other industries” (O_I) increases its GHG emissions by 30 tCO₂eq, and agriculture by 9 tCO₂eq in the *ET100* scenario compared to *Baseline*. In *SecRed*, GHG emissions of non-EU-ETS sectors reduce by definition of the scenario. Given the differences in prices for emission allowances within the EU-ETS, across scenarios, the service sector and O_I show the highest increase in emissions in *Eesub7* (overall percentage leakage relative to *Baseline*: 10%), and the lowest in *DoubleLearn* (percentage leakage: 7.9%). Increased flexibility in private consumption of fossil fuels (*FlexCons*) slightly decreases emissions, and thus the carbon leakage in these sectors. However, due to the increase in emissions from private households, the overall percentage leakage increases to 16% in *FlexCons*. In the following, we analyse the drivers of these inter-sectoral leakage effects, focusing on services and O_I.

The price effects of fossil fuels outside the EU-ETS mirror the contributions of electricity generation technologies towards mitigation within the EU-ETS across scenarios, which are discussed above (see Figure 7.2 for changes in input prices of fossil fuels and electricity in the EU). Even though coal prices outside the EU-ETS drop by almost 20% in *ET100* compared to *Baseline*, the smaller price effects on gas and oil are more important since they are the primary fossil energy sources outside the EU-ETS. Additionally, electricity prices need to be considered, as they play an important role in production prices outside the EU-ETS.

This becomes most evident in *DoubleLearn*, where across scenarios, gas prices show the highest decrease (3.9% compared to *Baseline*) and oil prices the smallest increase (1.1%). This result is coherent with the lower emissions, lower production and lower demand for fossil fuel input in EGas and EOil (see Table 7.4A). While services and O_I increase their gas consumption by 23% each in *ET100*, this increase is smaller in *DoubleLearn* (both sectors 15%), despite the lower gas price. This result can be explained by the development of electricity prices and its resulting changes in electricity consumption. Electricity prices increase substantially (over 40% on average in the EU compared to *Baseline*) with the cap tightening in *ET100*, and consequently electricity consumption in the sectors outside the EU-ETS decreases. This decrease in the electricity use is compensated by the direct use of fossil fuels, which is not levied with a CO₂ price in non-ETS sectors. However, double learning rates for renewables more than halve the electricity price effect to 19% (compared to *Baseline*). The relatively lower electricity prices induce a lower reduction in electricity consumption in *DoubleLearn* compared to *ET100* scenario (O_I: 5% vs. 8%; services:

4% vs. 7%). This also implies that less fossil fuels are used to substitute electricity. Thus, in *DoubleLearn*, electricity consumption is reduced less, and less electricity is substituted by direct fossil fuel consumption in the non-ETS sectors, despite lower prices for gas and oil. The opposite effect can be observed in *Eesub7*, where decreased flexibility of the electricity net aggravates this effect because of a higher allowance price in the EU-ETS and, thus, higher electricity prices. This leads to a higher substitution of electricity with fossil fuels and thus, to intersectoral leakage.

Among the non-ETS sectors, private consumption plays a unique role. In the GTAP data, private energy consumption includes direct household consumption of fossil fuels primarily for heating purposes, electricity consumption (including district heating), and fuel consumption for private mobility. In *Baseline*, coal has a share of 0.4% in total household energy consumption, gas of 9.4%, oil of 52.4% and electricity of 37.8% in the EU. The increases in electricity prices substantially reduce electricity consumption in all our scenarios, with the highest decrease (over 35% compared to *Baseline*) in *FlexCons*, which by design allows for an easier shift between energy sources for private consumption.

The lowest drop in electricity consumption appears in *DoubleLearn* (15%), where price effects on electricity are smaller. At the same time, we observe a substantial increase in GHG emissions from private consumption (21 tCO₂eq more than in *Baseline*) in *DoubleLearn*. This result is driven by higher gas consumption following the decrease in gas prices (-3.9%). In *FlexCons*, GHG emissions are even higher (81 tCO₂eq more than in *Baseline*) due to the easier substitution between different energy types and the resulting increase in consumption of all fossil fuels. Given that the GTAP sector subsumes very different energy systems for heating, household electricity and mobility, one might question the feasibility of higher substitutability between energy types. However, our results indicate that the observed increase in electricity prices and decrease in fossil fuels prices discourages the use of alternative energy sources like electric cars or non-fossil based heating systems.

The introduction of sectoral reduction targets for the non-ETS sectors (*SecRed*) avoids most of the substitution of energy inputs, despite similar increases in electricity prices compared to the *ET100* scenario. However, this comes at the expense of higher mitigation costs inside the EU-ETS. In all EU regions except EHC and GER, EU-ETS sectors increase their GHG emissions, although the allowance price is higher than in *ET100*. The effect of lower fossil fuel prices (see Figure 7.2, -

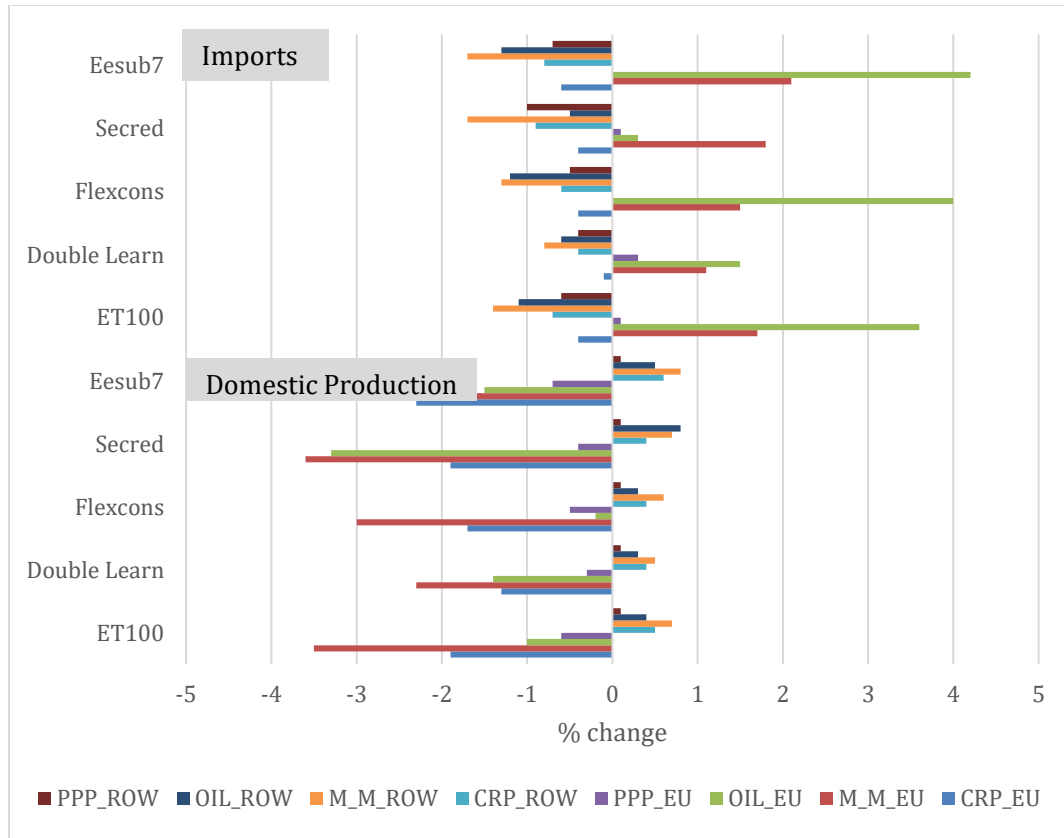
21.8% for Coal and -3.7% for Gas compared to *Baseline*) which result from lower demand in the now restricted non-ETS sectors, offsets the effect of higher allowance prices. As a consequence, EHC and GER, the countries with the highest share of coal-based electricity increase their share in climate mitigation within the EU-ETS. Total emissions (including emissions both inside and outside the EU-ETS) decrease between 14% (EHC) and 4% (ITA) in the EU regions, making *SecRed* the scenario with highest overall net reductions, as the imposed policy avoids the inter-sectoral leakage.

7.4.3 Effects outside the EU

In our model, regions are connected via trade and thus, the effects of the policies in EU are transmitted to the rest of the world. Since in our scenarios we do not implement additional mitigation policies outside the EU, the leakage rate for CO₂ emissions in non-EU regions amounts to 35% to 43% of the emissions abated in the EU. The largest components of the emissions increase come from the sectors ECoal (50%-70%), M_M (10%-20%) and EGas (10%-20%) sectors.

The main driving force behind the international leakage is the change in international fossil fuel prices following the decrease in demand for fossils after tightening the EU-ETS cap, which causes an increase in use of fossil fuels outside the EU. The largest drop in prices occurs in *DoubleLearn* (3.6% in COL, 1.8% in GAS, 0.7% in CRU, and 0.8% in OIL). Predominantly coal-based economies like China and India take advantage of the lower international fossil fuel prices by marginally reducing domestic production of coal and gas and increasing the now cheaper imports of these commodities. In China, coal imports increase by about 12%, while gas imports increase in the range of 0.2%-3% across scenarios. At the same time, we observe a shift from gas to coal-based electricity in all scenarios, with the highest increase of 1.3% in ECoal production in *FlexCons* and *Eesub7*. Even though prices decrease for coal are larger in *DoubleLearn*, the stronger increase of Ecoal production, and thus leakage effects, in these scenarios follows a relatively low decrease in gas prices (-0.2% in *FlexCons* and -0.4% in *Eesub7*) compared to *DoubleLearn* (-1.9%) (see Table 7.4A).

Figure 7.3: Percentage change in domestic production and imports of non-energy ETS sectors



In most non-energy ETS sectors, we see a displacement of production from the EU (with CO₂ pricing) to non-EU (without CO₂ pricing). Outside the EU, there is an increase in the production within the ETS sectors M_M, CRP, OIL and PPP. This production rise is coupled with an increase in EU's imports in sectors OIL (0.3% to 4.2%), M_M (1.1% to 2.1%) and PPP (0.02% to 0.3%), indicating that there is displacement of production for these sectors from the EU to non-EU regions (see Figure 7.3). Outside the EU, FSU experiences the highest increase in OIL (1.1% to 2.3%) and M_M (1.6% to 2.5%) production. The PPP sectoral production increases by a smaller percentage outside the EU (0.1% to 0.6%), with no single region leading.

7.5 Discussion and Conclusion

This study analyses the interplay between the EU-ETS allowance price and the development of renewable energy technologies. We characterize five policy settings for the EU in the CGE model

DART. Our results show that renewable energies, albeit not part of the EU-ETS, are strongly interconnected with the ETS allowance price and emissions.

On the one hand, a higher allowance price triggers an increased use of renewables in the EU. Within the individual EU countries, the electricity portfolio determines how the electricity sector and overall emission reductions (as electricity sectors typically dominate them) respond. Increasing allowance prices cause higher overall CO₂ reductions in EU countries with a high share of coal in their electricity portfolio. On the other hand, developments related to renewables play a vital role in the development of allowance prices and sectors inside the EU-ETS, especially in the composition of fossil-based electricity production. For example, increased learning in renewable electricity production technologies leads to higher competitiveness and market shares of renewables. In turn, lower marginal abatement costs within the EU-ETS causes lower allowance prices, and consequently, more coal-based electricity in the portfolio. If the integration of renewable electricity is hindered, e.g. due to grid restrictions, more conventional electricity is needed to meet the demand. Consequently, the allowance price is higher, indicating that marginal abatement costs for decarbonization are higher with reduced flexibility of electricity grids.

Higher allowance price within the EU-ETS increases carbon leakage, both inter-sectoral and international. High allowance prices go hand in hand with high electricity prices and reduced demand for fossil fuels from the ETS sectors to low prices for fossil fuels, particularly gas. Thus, inter-sectoral carbon leakage occurs by substituting fossil inputs from electricity to direct use in the sectors and regions outside the EU-ETS. Especially the service sector and industries outside the EU-ETS increase their emissions in case of higher allowance prices. Private households react similarly, indicating that the combination of high electricity prices and low fossil fuel prices also decreases their incentives for the transition to low carbon technologies in the absence of additional policies. Intensified production of renewable electricity technologies leads to cheaper electricity, decreasing this type of leakage effect. A binding cap on non-ETS sectors by design obstructs inter-sectoral leakage by avoiding the substitution of electricity with cheaper fossil fuels in non-ETS sectors, however, at the cost of higher prices within the EU-ETS.

On the international level, carbon leakage increases with higher EU-ETS allowance prices, mainly driven by lower international fossil fuel prices. The increase in emissions is the strongest in coal and gas-based electricity and the metals and minerals sectors. In the absence of climate action

outside the EU, we also observe a small increase in production of the ETS sectors outside the EU, indicating a displacement of these industries into other world regions.

Summing up, our study identifies three important policy findings. First, the interplay between the ETS and non-ETS sectors must not be neglected when policies aiming at emission reductions are implemented or amended. For example, when measures are taken to strengthen the stability of the EU-ETS market (e.g., the introduction of the Market Stability Reserve in 2019), accompanying policies for non-ETS sectors should be considered to avoid inter-sectoral carbon leakage. Second, inter-sectoral and international leakage can be reduced by strengthening the development of renewable energy technologies, whereas insufficient electricity grid integration has the opposite effect. Thus, the development of renewables and electricity grids should go hand in hand to maximize emission reductions. Third, our results identify fossil fuel prices as the main channel of international leakage. Thus, supporting renewables and electricity grid integration might be an alternative to the currently discussed Border Carbon Tax adjustments to avoid inter-national leakage.

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7.7 Appendix

Table 7.3A: Regional GHG emissions, renewable and coal share in baseline and % change in policy scenarios (rel. to baseline)

	Country	Total GHG Emissions						Share of Renewables in Total Electricity production						Share of Coal in Total Electricity production					
		GHG	Change in GHG Emissions in %					Share	Change in Share (in PP)					Share	Change in Share (in PP)				
			base-line	ET100	Double learn	Flex-cons	Sec-Red		Eesub7	base-line	ET100	Double learn	Flex-cons		Sec-Red	Eesub7	base-line	ET100	Double learn
EU - ETS countries	FRA	509	-4.8	-4.9	-4.3	-9.4	-4.6	5.0	0.7	3.4	3.4	0.8	0.6	2.2	-2.2	-2.1	-2.1	-2.2	-2.1
	GER	811	-27.7	-28.2	-25.5	-31.2	-26.6	18.7	19.2	28.6	28.6	19.5	17.9	43.6	-38.5	-36.7	-36.7	-39.5	-35.9
	ITA	456	-10.4	-12.5	-9.6	-13.9	-10.2	13.4	5.2	13.1	13.1	5.0	5.2	16.0	-15.0	-13.3	-13.3	-15.3	-14.1
	GBR	587	-13.2	-15.5	-11.9	-18.9	-12.3	14.9	8.0	22.8	22.8	7.7	7.2	22.8	-18.7	-17.3	-17.3	-19.5	-17.3
	BLX	362	-6.7	-7.4	-6.0	-10.7	-8.1	9.6	2.5	8.0	8.0	2.4	3.2	25.7	-12.7	-11.8	-11.8	-12.8	-16.9
	SPO	431	-16.8	-16.8	-16.2	-20.0	-17.2	22.7	8.2	11.6	11.6	8.1	8.5	20.2	-19.2	-17.2	-17.2	-19.4	-18.6
	SCA	293	-7.7	-8.1	-7.2	-11.0	-7.3	8.9	0.8	5.1	5.1	0.8	0.7	4.3	-4.3	-4.2	-4.2	-4.3	-4.1
	EHC	839	-20.0	-18.4	-17.5	-31.0	-20.6	7.2	5.7	10.5	10.5	5.8	6.2	63.9	-27.2	-21.6	-21.6	-28.9	-27.9
	ELC	498	-11.7	-11.9	-10.5	-16.0	-11.1	7.3	3.7	10.5	10.5	3.8	3.2	15.7	-14.7	-13.2	-13.2	-14.9	-13.8
Countries outside EU-ETS	USA	6100	0.3	0.4	0.3	0.7	0.3	2.9	0.0	0.0	0.0	0.0	0.0	43.2	0.1	0.0	0.0	0.1	0.1
	CAN	691	0.9	0.9	0.8	1.6	1.0	1.6	0.0	0.0	0.0	0.0	0.0	12.2	0.4	0.3	0.3	0.4	0.4
	RAXB	2057	0.9	0.8	0.8	1.2	1.0	1.3	0.0	0.0	0.0	0.0	0.0	31.0	0.3	0.2	0.2	0.2	0.3
	RUS	2268	1.0	0.9	0.9	1.1	0.9	0.0	0.0	0.0	0.0	0.0	0.0	15.3	0.9	0.8	0.8	0.8	0.8
	FSU	1287	1.6	1.2	1.5	1.8	1.9	0.1	0.0	0.0	0.0	0.0	0.0	39.7	0.1	-0.3	-0.3	-0.3	0.3
	CPA	10016	0.8	0.5	0.8	0.7	0.8	1.5	0.0	0.0	0.0	0.0	0.0	78.8	0.3	0.2	0.2	0.2	0.3
	IND	3038	1.2	1.0	1.2	1.0	1.2	2.4	0.0	0.0	0.0	0.0	0.0	66.4	0.6	0.3	0.3	0.3	0.6
	LAM	3093	0.6	0.5	0.5	0.8	0.6	0.4	0.0	0.0	0.0	0.0	0.0	4.8	0.3	0.3	0.3	0.3	0.3
	PAS	3800	1.1	1.0	1.1	1.3	1.1	0.2	0.0	0.0	0.0	0.0	0.0	33.3	1.4	1.1	1.1	1.1	1.2
	MEA	3487	0.5	0.5	0.5	0.7	0.6	0.6	0.0	0.0	0.0	0.0	0.0	8.0	0.6	0.5	0.5	0.5	0.6
AFR	1937	0.7	0.6	0.7	0.9	0.8	0.0	0.0	0.0	0.0	0.0	0.0	60.2	0.9	0.8	0.8	0.8	0.9	
Summary	EU	4787	-15.0	-15.4	-13.7	-20.3	-14.9	12.2	5.9	12.2	12.2	5.9	5.7	24.2	-18.8	-17.1	-17.1	-19.3	-18.4
	Rest of the World	37774	0.8	0.7	0.7	0.9	0.8	1.4	0.0	0.0	0.0	0.0	0.0	43.7	0.4	0.2	0.2	0.2	0.4
	World	42560	-1.0	-1.1	-0.9	-1.5	-1.0	3.1	0.4	1.3	1.3	0.4	0.4	40.7	-1.4	-1.6	-1.6	-1.7	-1.4

Table 7.4A: Percentage change in regional electricity, coal and gas consumption in policy scenarios relative to baseline

		Electricity Consumption					Coal Consumption					Gas Consumption				
		% Change in Electricity Consumption					% in Coal Consumption					% in Gas Consumption				
		ET100	Double learn	Flex-cons	Sec-Red	Eesub7	ET100	Double learn	Flex-cons	Sec-Red	Eesub7	ET100	Double learn	Flex-cons	Sec-Red	Eesub7
Price Allowances EU-ETS		100	71	90	106	126	100	71	90	106	126	100	71	90	106	126
EU-ETS sectors	OIL	-10.8	-6.2	-8.4	-14.8	-12.5	-0.6	-1.1	0.3	-3.3	-1.2	-1.7	-3.2	-1.5	-3.5	-2.8
	CRP	-15.3	-8.0	-13.2	-16.6	-17.0	-83.6	-77.1	-81.7	-84.7	-87.2	-26.5	-19.6	-24.6	-26.9	-31.6
	M_M	-5.9	-1.6	-4.6	-6.7	-6.2	-74.6	-67.3	-72.4	-75.9	-79.2	-29.4	-23.7	-27.6	-30.0	-34.5
	PPP	0.1	1.5	0.4	-0.1	0.5	-63.9	-57.3	-61.6	-65.3	-69.3	-18.2	-16.2	-17.4	-18.0	-22.5
	COL	-51.3	-45.3	-46.9	-59.3	-51.6	-0.8	-5.4	1.1	-10.9	3.9	-32.3	-31.9	-29.3	-41.5	-27.8
Sectors outside EU-ETS	GAS	-18.1	-13.0	-15.1	17.2	-20.5	43.2	30.0	41.3	74.8	40.6	3.3	0.2	3.4	-29.8	4.0
	CRU	-13.0	-7.3	-11.2	-15.1	-14.2	30.0	22.2	29.3	29.2	30.9	5.0	3.2	4.4	5.7	5.7
	AGR	-15.5	-8.4	-13.2	-12.2	-17.4	51.4	42.2	47.0	-61.8	53.1	12.0	8.4	10.2	-11.7	14.5
	ctl	-13.9	-7.6	-11.9	-9.5	-15.5	65.7	50.8	58.9	-72.5	70.4	13.8	10.3	11.7	-24.1	16.6
	otp	-20.2	-11.3	-17.6	-15.5	-22.5	41.3	35.8	38.5	-52.1	41.6	8.1	7.7	7.1	-28.2	9.7
	watp	-21.4	-12.0	-18.7	-17.9	-23.9	37.7	35.0	34.7	-71.4	36.3	5.9	6.9	5.0	-49.4	6.9
	O_I	-8.2	-4.7	-7.1	-3.8	-9.1	68.6	50.3	61.6	-62.1	73.0	23.1	14.5	19.7	-10.5	27.2
	SVCS	-7.2	-4.0	-6.2	-3.4	-8.1	75.8	55.7	67.6	-65.3	82.1	23.3	14.5	19.8	-11.4	27.4
	Direct consumption	-28.3	-15.4	-35.7	-29.8	-31.7	28.9	27.6	84.3	-10.6	27.8	2.1	4.6	12.6	-6.3	1.9

8. Conclusion

Climate change is one of the critical challenges that the world faces today. The global nature of the impacts of climate change makes it a topic of interest for policymakers worldwide. Reducing greenhouse gas (GHG) emissions, i.e. decarbonisation, is essential to slowing climate change. Since 2015 most of the policy discussions about mitigation have been centred around the Paris Agreement, the latest GHG mitigation pact adopted by 195 countries. Policymakers need tools to assess the economic and environmental impacts of proposed climate and energy policies. To this end, ex-ante policy modelling with computable general equilibrium (CGE) models remains a widely used tool.

This dissertation investigates the role of cooperation and coordination between regions and sectors in implementing climate change policies and their effects on economic and environmental outcomes. The thesis contributes to the literature on ex-ante modelling of climate policies by:

1. Providing both qualitative insights from ex-ante modelling literature on carbon pricing and quantitative insights using meta-regression analysis.
2. Developing a method for baseline calibration of dynamic CGE models.
3. Empirically conducting ex-ante evaluations of quantifying the impacts of specific cooperative carbon pricing instruments using the global CGE model - DART.

Section 8.1 highlights the key results and contributions that are derived from the different chapters by categorising the results according to the instrument of cooperation along with specific discussion on methodological contribution in Section 8.1.3. Subsequently, Section 8.2 highlights the key policy implications and Section 8.3 discusses the work's limitations and direction for future research.

8.1 Main findings and contributions

Chapter 2 provides a comprehensive qualitative literature review, primarily from the last two decades, of carbon pricing and the gains that can be achieved by regional and sectoral cooperation and coordination in implementing climate policies. At the global scale, all forms of cooperation mechanisms can potentially deliver economic benefits and environmental gains. However, the

regional and sectoral distribution of impacts strongly depends on the policy conditions. This chapter contributes to the modelling literature by providing a systematic review of the vast literature and summarising it into key points about where the literature agrees and where the evidence is ambiguous. Chapter 3 uses meta-regression analysis (MRA) to examine the effect that structural characteristics of CGE models have on the model generated abatement costs. We also quantitatively explore the impact of policy features, i.e. the extent of cooperation between participating regions and sectors and mitigation targets on the abatement costs of fulfilling the CO₂ reductions as stated in the Nationally Determined Contributions (NDC). The contribution of this chapter lies in its ability to add-on to models results by using empirical tools to provide robust results. Finally, chapter 4 offers a methodological contribution to the literature by proposing a method for calibrating the baselines of dynamic CGE models using Bayesian estimation techniques and metamodeling.

As part of the empirical contributions of the dissertation, we model three instruments of cooperation using our own Computable General Equilibrium (CGE) model – DART, with regard to the Paris Agreement. Chapter 5 to Chapter 7 present the modelling results and in addition to the modelled cooperation tool the chapters other specific research questions are also investigated.

Chapter 5 models regional and globally harmonised carbon prices. This chapter also models the linked carbon markets with different assumptions on the allocation of emission rights: grandfathering versus carbon egalitarianism-based allocation. This chapter makes two additional contributions to the analysis of the economic costs of reaching the NDC pledges. First, it disaggregates the welfare costs into the direct mitigation and indirect costs arising due to international market changes. Second, it estimates the monetary flows from the developed countries to the developing countries via the carbon markets if there is a global carbon market and the allowances are distributed in proportion to regional population share, i.e. maintaining the principle of carbon egalitarianism.

Chapter 6 concentrates on sub-global cooperation between China and the EU, assuming a joint ETS between the two regions while the rest of the world has domestic carbon markets. This common EU-China carbon market is modelled with variations in the following three assumptions - the share of allowances that are traded, the existence of transfer payments from EU to China and, changes in trade barriers. In both Chapter 5 and Chapter 6, the regional and global mitigation

targets reflect the CO₂ reduction targets from the NDC pledges. The analysis of this chapter is valuable since it provides a detailed analysis of different policy structures of linking relative to the rest of the CGE literature. In addition, results of the EU-China linking designs are also tested for sensitivity to changes in trade barriers. Lastly, Chapter 7 highlights the importance of coordinated policy design within a region to avoid carbon leakage when only a part of the GHG emissions face a carbon price. Specifically, we model complementary policies in non-ETS sectors, changes in the economy's structural characteristics, and behavioural changes in consumer response to energy prices. This chapter contributes by investigating the role of structural changes and behavioural changes on EU-ETS and comparing the results from these exogenous changes in a coherent framework.

8.1.1 Global coordination

Based on the estimates from the literature in Chapter 2, with the NDC pledges as the target, relative to unilateral ETS a global carbon market would reduce the cost of fulfilling the NDCs by two-thirds, i.e. about \$229 billion by 2030. The estimates of MACs to reach the NDC targets with globally linked carbon markets lies between \$5/tCO₂ to \$58/tCO₂ in 2030 with the average price across studies being \$19/tCO₂ and the median estimate of \$14/tCO₂. The estimate from our policy modelling (shown in Chapter 5) shows the MAC estimate in 2030 to be about \$16/tCO₂. Among the comparable regions, the DART estimates of regional MACs for the USA, the EU and Canada are lower than the median values from the literature, while those for India, China, Russia, Japan, Australia and New Zealand are lower than the median values.

The divergence of the results from DART to the averages from the literature makes one wonder about why generally the results across studies differ. It is difficult to precisely trace the reasons behind the differences in marginal abatement costs (MAC) across different models. This is because models used in different studies diverge in regional and sectoral aggregation, assumptions about exogenous parameters (like elasticities, growth of labour force, productivity, energy efficiency), the time horizon of models, policy targets and, the outputs presented in the paper. To follow up on this research question, in Chapter 3, we use the consistent modelling setup established within the EMF36 cross-model study to assess the role of structural model variables in determining the MAC estimates from models. Using meta-regression analysis (MRA), our results show that structural features of models like regional disaggregation and differentiation between fossil-based and

renewable electricity, choosing a dynamic model, and using the GTAP Armington trade elasticities increase the MAC estimates. At the same time, the inclusion of endogenous technological change and modelling labour frictions via unemployment decrease the MAC estimates in models. Results also reveal that fully globally linked carbon markets, i.e. globally harmonised carbon prices, can lower MACs by 45% relative to regionally unilaterally designed carbon markets.

8.1.2 Sub-global coordination

There is sufficient difference in the MACs across regions, and therefore, another policy design that countries could explore is the voluntary linking of sub-global carbon markets. Evidence from the literature shows that sub-global cooperation reduces global abatement costs though by a lower value than fully global cooperation. The regression results from Chapter 3 confirms this and empirically estimates the cost reduction from global cooperation (45% reduction in MAC). Additionally, from the MRA, we can identify carbon markets for which statistically significant global reductions in MAC are realised. Our results show that only two markets, i.e. the globally linked carbon market and regionally linked carbon markets consisting of China, Japan, and South Korea, lead to statistically significant reductions in global MACs.

Chapter 6 examines the sub-global linking between the EU ETS and Chinese ETS. Though the results from Chapter 3 do not indicate robust reductions in global MACs, we still observe significant impacts on regional MACs of EU and China, which makes this potential cooperation of interest. The contribution of Chapter 6 lies in the detailed consideration of the different designs that could be used in linking the two markets. Modelling results from DART show that with a fully linked carbon market between China and EU, the regional MAC of EU would decrease by 82%. In comparison, China's MAC will increase by 29% since there are relatively cheaper abatement options relative to the EU. The low cost of abatement in 2030 in China relative to Europe is seen in Chapter 2 and Chapter 5. When compared to the (significant) coefficients from MRA, the percentage changes in the regional MACs as derived from DART are higher for EU (MRA shows a reduction of 36%) and lower for China (MRA shows an increase of 45%).

Overall it can be seen that in this dissertation we play to the strengths of CGE modelling as well as meta-regression analysis and together they provide robust results.

8.1.3 Policy coordination within a region

Chapter 7 focuses on climate policy coordination within a region to mitigate carbon leakage when only a share of the total regional GHG emissions are priced. Using the case of the EU ETS, the chapter discusses the role played by complementary policies in the unregulated sectors and behavioural changes in consumer decision making. The rationale behind ensuring policy coordination in a region is supported by the fact that there are economic linkages between the ETS sectors and the rest of the regional and global economy. These economic interlinkages indirectly transmit the effects of the ETS policy to sectors that are not regulated and vice versa, and thus, could impact the broader economic and environmental targets of the EU. This chapter explores the effects of structural changes in the unregulated part of the economy on existing policies and behavioural changes in consumers. Key results show that with the EU ETS in place, in the absence of complementary policies in unregulated sectors, the highest inter-sectoral leakage is observed when consumers preferences flexibly adapt to changes in energy prices. However, the leakage can be mitigated with reduction targets set in the unregulated sectors in the EU. Technological development in renewables and better integration within the electricity grid also mitigate carbon leakage.

8.1.4 Other methodological contributions

The dynamics of the baseline of CGE models affects the cost estimates (Fischer and Morgenstern 2006; Kuik et al. 2009). Chapter 4 proposes a method for calibrating the baseline dynamics of CGE models by developing a relatively objective method that is largely objective and less reliant on expert judgement. In addition, more transparency and replicability in baseline development can improve the interpretation of results from modelling studies. Studies (Kuik et al. 2009) have considered the baseline emission pathway as a structural model variable in MRA to explain the differences in abatement costs across models. However, in the current work, we do not include baseline emissions as a structural variable as by design, all models were calibrated to the same baseline emission pathways, thereby eliminating heterogeneity in the variable across models.

8.2 Limitations and scope for future research

Indeed, the CGE modelling approach has limitations that also apply to the DART model used in our policy analysis. (1) CGE models represent a highly stylised version of the world and ignore

potential unobserved heterogeneity at the sub-regional and sub-sectoral levels (Alexeeva-Talebi et al. 2012). (2) Policies in CGE models are often modelled assuming the first-best-economic and policy world. However, this assumption is not coherent with the typical piecemeal approach of policy-making processes and institutes seen in practice. (3) Results from CGE analysis are subject to parametric uncertainty. (4) The modelling of policies in the CGE framework ignores some of the practical challenges of implementing climate policies (e.g., monitoring, reporting and verification of ETS, transaction costs), distribution issues (e.g., cost incidence for consumers and businesses, equity, just transition), political issues (e.g., public perception of carbon prices, influence of lobby groups) and legal issues (e.g., compatibility with the WTO rules). (5) A specific limitation of DART lies in the representation of total emissions. The CO₂ emissions accounted for in DART only cover the energy related end-of-pipe emissions, i.e. CO₂ emissions from burning fossil fuels, and exclude other GHGs as well as emissions from forestry and other land-use, process emissions and fugitive emissions.

There is clearly no single silver bullet that would accelerate action on climate change. Nevertheless, by gauging where the literature agrees and where the evidence is unclear informs us about where the future research should be directed. Generally, the linking of CGE models to political economy models could provide a promising direction for future research and would address some of the limitations addressed above. Integrating more econometric approaches into CGE modelling could help reduce the parametric uncertainty. This dissertation provides one example for such an integration in the calibration of CGE models but there is certainly scope for further developments in this direction. Specifically, with regard to future improvements with our CGE model DART we are already in the process of addressing some of the limitations. We have integrated non-CO₂ emissions (seen in Chapter 7) and GHG emission from land-use and thus, all of the upcoming work would consider a broader group of emissions. There is also on-going work to link DART with a political economy bargaining model from CAU which would create an integrated framework to assess economically and politically feasible policy options.

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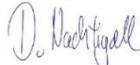
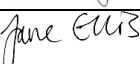
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The economic and environmental benefits from international co-ordination on carbon pricing: A review of economic modelling studies

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