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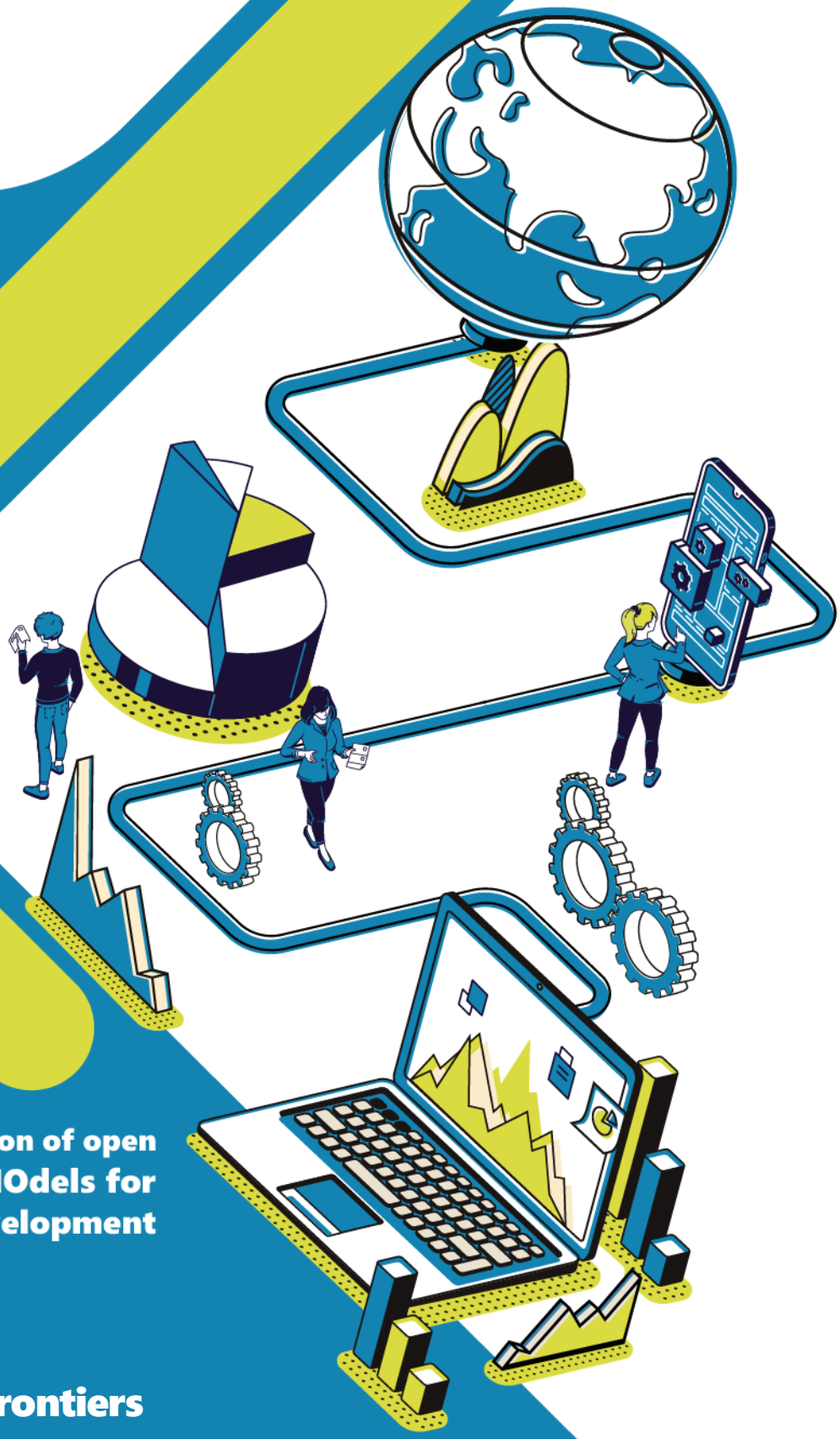

Delivering the next generation of open Integrated Assessment MOdels for Net-zero, sustainable Development

D5.5 – Stretching the frontiers

WP5 – Apply & Explore

Funded by the European Union

30/10/2026

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EC Summary Requirements

1. Changes with respect to the DoA

No changes with respect to the work described in the DoA.

2. Dissemination and uptake

The results of this deliverable are primarily relevant to researchers working on integrated assessment modelling, energy systems, macroeconomics, and climate policy, particularly those focussing on industrial decarbonisation pathways, socio-economic transitions, distributional impacts, and behavioural change. The findings are also relevant to policymakers, industry stakeholders, financial institutions, and civil society organisations involved in designing and implementing climate change mitigation strategies and just transition policies, since the questions addressed herein were co-produced with relevant stakeholders as part of the project's transdisciplinary process.

The report demonstrates the value of advancing and linking IAM frameworks to better represent circular economy measures, household heterogeneity, labour and financial market dynamics, consumer behaviour, and societal preferences. These developments provide new insights into the economic, social, and political dimensions of the low-carbon transition that are often insufficiently captured or overlooked by conventional modelling approaches.

3. Short summary of results (<250 words)

This report features analysis from four different scenario studies responding to pertinent stakeholder-informed research questions, using models and modules developed and linked during the DIAMOND project. The four studies include: the role of circular economy measures in decarbonisation pathways (Chapter 2); the distributional impacts of net-zero targets in Europe (Chapter 3); the implications of labour market and financial dynamics, and consumer behaviour for climate policy (Chapter 4); and the impact of societal preferences and trends on climate action (Chapter 5). Chapter 2 identifies a strong role for circular economy measures across three key basic materials sectors, stressing the need for international cooperation to maximise benefits and demonstrate how such actions can reduce mitigation costs. Chapter 3 highlights the importance of introducing household heterogeneity into climate policy analysis to provide insights into policy effectiveness of different mitigation options, and their distributional impacts, revealing several interconnections between income distribution and mitigation, concerning the impact of changes in income structures on emissions as well as distributional impacts in different mitigation pathways, while demonstrating the importance of behavioural (beyond structural) heterogeneity and sensitivity to different datasets. Chapter 4 explores how frictions in labour, capital and consumer technology markets change transition pathways and their distributional outcomes, and which policy instruments can be used to address these frictions; key insights emerge on impacts on labour force from the transition, technology deployment from financing costs, and distributional impacts and targeted support for cleantech roll out. Chapter 5 focuses on better integrating societal preferences in modelling analysis, highlighting implications for EV rollout when behavioural preferences are integrated, helping to identify more effective policy measures to accelerate this rollout. Collectively, the report demonstrates the value of additional IAM development and linking to generate new insights for decision makers and other stakeholders on how to accelerate the low-carbon transition.

4. Evidence of accomplishment

This report.

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Preface

DIAMOND will update, upgrade, and fully open six Integrated Assessment Models (IAMs) that are emblematic in scientific and policy processes, improving their sectoral and technological detail, spatiotemporal resolution, and geographic granularity. It will further enhance modelling capacity to assess the feasibility and desirability of Paris-compliant mitigation pathways, their interplay with adaptation, circular economy, and other SDGs, their distributional and equity effects, and their resilience to extremes, as well as robust risk management and investment strategies. This will be done via integration of tools and insights from psychology, finance research, behavioural and labour economics, operational research, and physical science. The project will develop a transdisciplinary scientific approach to legitimise the implementation process and co-create research questions that stretch the frontiers of climate science, as well as establish vibrant communities of practice to transparently open model enhancements and to develop capacities, thereby lowering the entrance barriers to the established IAM community.

ICCS	INSTITUTE OF COMMUNICATIONS AND COMPUTER SYSTEMS	EL
BC3	ASOCIACION BC3 BASQUE CENTRE FOR CLIMATE CHANGE - KLIMA ALDAKETA IKERGAI	ES
CESAR	KRATENA KURT	AT
CICERO	CICERO SENTER FOR KLIMAFORSKNING	NO
CYI	THE CYPRUS INSTITUTE	CY
E4SMA	ENERGY ENGINEERING ECONOMIC ENVIRONMENT SYSTEMS MODELING AND ANALYSIS SRL	IT
HOLISTIC	HOLISTIC IKE	EL
COMILLAS	UNIVERSIDAD PONTIFICIA COMILLAS	ES
ISINNOVA	ISTITUTO DI STUDI PER L'INTEGRAZIONE DEI SISTEMI (I.S.I.S) - SOCIETA'COOPERATIVA	IT
SEURECO	SEURECO SOCIETE EUROPEENNE D'ECONOMIE SARL	FR
UM	UNIVERSITEIT MAASTRICHT	NL
ESMIA	ESMIA CONSULTANTS INC.	CA
USMF	THE UNIVERSITY OF MARYLAND FOUNDATIION INC	US
UMD	UNIVERSITY OF MARYLAND	US
EPFL	ECOLE POLYTECHNIQUE FEDERALE DE LAUSANNE	CH
ETH	EIDGENOESSISCHE TECHNISCHE HOCHSCHULE ZUERICH	CH
UNIBAS	UNIVERSITAT BASEL	CH
Imperial	IMPERIAL COLLEGE OF SCIENCE TECHNOLOGY AND MEDICINE	UK
Oxford	THE CHANCELLOR, MASTERS AND SCHOLARS OF THE UNIVERSITY OF OXFORD	UK
UCL	UNIVERSITY COLLEGE LONDON	UK

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Executive Summary

This report covers four separate scenario studies that have been undertaken under WP5 of DIAMOND, demonstrating how the IAM development activities undertaken and subsequent module development and linking allow for new and innovative scenarios analysis. The resulting scenario modelling presented here aims to respond to stakeholder-informed research questions that have been co-designed through a transdisciplinary process of engagement that has run throughout the duration of the project (under WP2). This has helped ensure that the scenarios of focus are societally relevant and robust and has involved proposing, testing, and refining research questions with a range of stakeholders.

Circular economy measures can support more cost-effective decarbonisation of basic materials sectors

Chapter 2 assessed the role that specific circular economy (CE) measures can play in supporting decarbonisation goals, both at the EU level and globally. It centres around scenarios that explore the role of CE policy packages differentiated by ambition, and their implementation in the EU and in partnership with other country partners. The analysis focuses on the application of OMNIA (a new global IAM developed in DIAMOND) coupled with the CGE model ENGAGE, as well as the comparison of scenarios modelled with two other new models of the DIAMOND project, GCAM-Europe and OPEN-PROM.

The research finds that CE measures lead to a wider portfolio of mitigation measures that can enable additional GHG reductions across key basic material sectors. Relative to a scenario with no CE measures, additional GHG emission reductions range between 32-37% by 2050. However, wider international co-operation on CE measures with key international partners is key to realising larger global GHG reduction benefits. This includes enhanced coordination across international trade sectors to amplify the effectiveness of CE measures, and a focus on production centres of China and India, given their current leading position in the production of basic materials, which is expected to continue in the long term.

The scenario modelling also shows that CE measures can lead to energy-system cost reductions across basic material sectors, due to an increase in the share of lower-cost secondary production and reduced overall levels of production. This could help reduce the costs of decarbonisation, as reflected in lower carbon prices, helping avoid expensive and hard-to-scale mitigation options. The study also usefully highlights the wider co-benefits of CE policies, not only in respect of supporting climate mitigation objectives—but also in promoting resource efficiency and waste reduction in basic materials, and in lowering costs of economic activities using these materials. Decarbonisation objectives can help drive circularity action, in addition to CE measures playing a key role as part of the set of mitigation actions.

Representing household heterogeneity in IAMs shows multiple interconnections between income structures, their dynamics, and mitigation paths

Chapter 3 deals with the interlinkages between income distribution, mitigation pathways, and emission reduction policy instruments for the EU. Beyond the existing literature, the role of shifts in income distribution on households' energy demand as well as the dynamic impacts of mitigation policy on long-run income structure are explored. One new aspect attempted was to test the sensitivity of results for different household data sets. The results corroborate the general result of regressivity of pure carbon pricing (without revenue recycling) and highlight the importance of interaction between income structures and emission mitigation in a consistent scenario framework.

Improved disaggregation of the household sector in IAMs reveals the interlinkages between mitigation policies and pathways and income distribution. Notably, we highlight that the economic burden and benefit of mitigation

policies can be heterogenous across household types, while long-run changes in the income levels of different household groups feedback on emission levels and therefore on required mitigation efforts. This is first shown in simulations using GCAM-Europe with household heterogeneity to represent different income structures and income distribution dynamics within the well-defined climate scenarios SSP1, SSP2, and SSP3. The income shifts between household groups have an influence (feedback) on residential energy demand and emissions that (i) shows significant heterogeneity between EU countries in all scenarios and (ii) can lead to different signs of change between scenarios for energy demand and emissions.

In simulations with NEMESIS with structural and behavioural household heterogeneity, a carbon price that rises to €854/t CO2 in 2050, affects lower- and middle-income households more than higher-income households. In 2045, disposable income decreases by 0.95% for the first and 1.12% for the second decile, compared with only 0.59% for the tenth decile. The burden, measured as the share of carbon tax payments in total household consumption expenditure, systematically decreases with income and reaches a maximum around 2040–2045 before progressively declining towards 2060, consistent with households' adjustments in energy consumption. As this burden over time decreases much more for the highest income group than for the low-income groups, revenue recycling should include targeted support for low-income groups to adjust their energy demand.

Improving understanding of how labour dynamics, financing of technology, and consumer behaviour impacts EU energy transition objectives

Chapter 4 examines how frictions in labour, capital, and consumer technology markets change transition pathways and their distributional outcomes, and which policy instruments act on these frictions. It applies the three modules developed in DIAMOND Deliverable D4.5 to their host models: a directed search labour module linked to GEMINI-E3 EU, a finance module with maturity-dependent costs of capital linked to CLEWs-EU and NEMESIS, and the HATT heating technology adoption module linked to GCAM-Europe.

First, key insights emerge from the analysis on labour markets. Representing search frictions and limited labour mobility in GEMINI-E3 EU changes who bears the cost of the transition more than its aggregate cost. The mobility regime changes EU GDP in 2050 by at most 0.1 percentage point, but wage gaps between contracting and expanding power sectors are up to two and a half times larger when mobility is low. In Germany, certifying the skills of displaced fossil-power workers lowers their unemployment (in 2040 from 5.6% to 3.3% at the highest level, rigid regime); a retraining subsidy alone does not.

The research also reveals how financing conditions shape the technology mix. Replacing a uniform 7.5% discount rate with differentiated empirical WACCs raises EU installed capacity in CLEWs-EU by 2.8% in 2050, and capping renewable WACCs shifts investment towards wind. Doubling State Investment Bank funding roughly halves funding constraints for biomass and offshore wind and lowers their WACCs by 1.3-1.4 percentage points. Green quantitative easing has almost no effect, because the mature renewables it supports are rarely constrained.

Finally, in relation to consumer behaviour in the transition, the research finds that heterogeneous households respond differently. Gas heating becomes concentrated among low-income households, the lowest of which cannot afford a heat pump without support. A carbon tax combined with a heat pump subsidy that is targeted by income increases access for low-income households but raises the EU heat pump share in 2050 only from 12.4% to 13.7%. This narrows the adoption gap between rich and poor households but only slightly. Removing the affordability constraint is necessary but not sufficient on its own for adoption by low-income households.

More realistic EV deployment in IAMs based on explicit consumer preferences helps improve assessment of necessary policy support for accelerating uptake

Chapter 5 describes the effects of linking three IAMs (CLEWs-EU, GCAM-Europe, and OMNIA) with a newly

developed behavioural module on car purchase decisions that is based on a large-scale experimental data collection process. The comparison of model runs with and without the soft link highlights shortcomings of current modelling practices including unrealistically high EV adoption rates that are emphasised under disruptive events. The IAM outputs combined with findings from an ABM point to purchase price subsidies as an effective measure to stimulate the EV market.

A key finding is that when soft-linking the behavioural module of car choices with IAMs, EV adoption reduces under binding climate targets in CLEWs-EU and OMNIA, but not GCAM-Europe, although adoption patterns vary between countries. Lower EV adoption is compensated elsewhere in the system, mostly through Carbon Capture and Carbon Removal. This compensation mechanism indicates the necessity to politically intervene in the transportation sector given the limited capacity potential of Carbon Capture and Removal technologies, with purchase price subsidies as a promising lever.

Sustained disruptive events such as uncertainty of gasoline and electricity prices as well as tariffs on EVs further decrease EV adoption when considered in the soft-linking approach. Policies are needed to buffer these effects of crises. In uncertain periods of disruption, measures lowering purchase prices appear more robust than instruments targeting vehicle operating costs, such as carbon taxes. The ABM allows more fine-grained, income-specific analyses that are currently not possible in the collaborating IAMs, but practically feasible with the behavioural module. Targeted support for lower-income households may be needed where disruption widens adoption gaps.

The research finds that explicitly representing non-monetary, psychological behavioural determinants in IAMs allows for a more accurate modelling of soft policies or interventions. For example, our psychological analyses reveal the importance of social norms in car choices, which could be targeted by interventions such as communication programs or stimulating exchange between adopters and non-adopters.

Cross-Cutting Remark: Collectively, the report demonstrates the value of further developing and linking IAMs to better capture the economic, circular, behavioural, and distributional factors shaping the low-carbon transition, improving the realism of cost and technology uptake estimates. These advances provide decision makers and other stakeholders with new insights into how coordinated and targeted policies can address barriers, improve cost-effectiveness, and accelerate a more equitable transition.

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1 Introduction

1.1 Overview of deliverable

This report covers four separate scenario studies that have been undertaken under WP5, specifically task 5.4 *Stretching the frontiers – user-driven scenarios building on expanded modelling framework*. These studies demonstrate the use of new open models, developed under WP3, their extension or linkage to other models, under WP4, and application to enable new and innovative scenario analysis. The scenario analyses are summarised in Table 1.1, indicating the new models used and the additional development undertaken to enable the analyses.

Crucially, all scenarios presented in this deliverable have been co-designed through an engagement process that has run throughout the duration of the DIAMOND project. This process, to ensure scenarios of focus are societally relevant and robust, has involved proposing, testing and refining stakeholder-informed research questions with a range of stakeholders, as reported under WP2. The full list of the stakeholder-informed research questions can be found in D2.5, while the approach to transform them into the final research questions pursued here (and which are described in detail in each section) can be found in D5.2.

Table 1.1. Summary of scenario studies in the report

Scenario topic	New models used (WP3)	Additional development (WP4)	Report section
Circular economy measures to support decarbonisation goals	OMNIA, GCAM-Europe, OPEN-PROM	ENGAGE model extension, and linkage with OMNIA	2
Income distribution impacts of net-zero targets in Europe	GCAM-Europe, NEMESIS	Integration of the DIAMOND household heterogeneity dataset and comparison with the relevant dataset of EUROSTAT	3
Financial and labour market frictions and consumer technology adoption.	GEMINI-E3-EU, NEMESIS, CLEWs-EU and GCAM-Europe	Interactions with modules adding financial markets, labour markets and consumer adoption decisions and policies addressing them.	4
Interplay between disruptive events and behavioural preferences in the car market	CLEWs-EU, GCAM-Europe, OMNIA	Behavioural module development and disruptive event extension, and soft-link with three IAMs	5

1.2 Structure of the report

The report is structured into four main scenario analysis chapters (2-5), with chapter 6 summarising the key findings from each.

Chapter 2 describes an assessment of the role that specific circular economy (CE) measures can play in supporting decarbonisation goals, both at the EU level and globally. It centres around scenarios that explore the role of CE policy packages differentiated by ambition, and their implementation in the EU and in partnership with other country partners. The analysis focuses on the application of OMNIA, a new global IAM coupled with the CGE model, ENGAGE, and comparison of scenarios modelled with two other new models, GCAM-Europe and OPEN-PROM.

Chapter 3 deals with the interlinkages between income distribution, mitigation pathways and emission reduction policy instruments for the EU. Beyond the existing literature, the role of shifts in income distribution on households' energy demand as well as the dynamic impacts of mitigation policy on long-run income structure are explored. One new aspect is to test the sensitivity of results for different household data sets. The results corroborate the general result of regressivity of pure carbon pricing (without revenue recycling) and highlight the importance of

interaction between income structures and emission mitigation in a consistent scenario framework.

Chapter 4 examines how frictions in labour, capital and consumer technology markets change transition pathways and their distributional outcomes, and which policy instruments act on these frictions. It applies the three modules developed in DIAMOND Deliverable D4.5 to their host models: a directed search labour module linked to GEMINI-E3 EU, a finance module with maturity-dependent costs of capital linked to CLEWs-EU and NEMESIS, and the HATT heating technology adoption module linked to GCAM-Europe.

Chapter 5 describes the effects to linking three IAMs - CLEWs-EU, GCAM-Europe, OMNIA – with a newly developed behavioural module on car purchase decisions which is based on a large-scale experimental data collection. The comparison of model runs with and without the soft-link highlights shortcomings of current modelling practices including unrealistically high EV adoption rates which are emphasized under disruptive events. The IAM outputs combined with findings from an ABM point to purchase price subsidies as an effective measure to stimulate the EV market.

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2 The role of circular economy measures in decarbonisation pathways

2.1 Introduction

This section of the deliverable focuses on the application of Integrated Assessment Models (IAMs) to the assessment of the role that circular economy (CE) measures can play in achieving both EU and global decarbonisation targets. By CE, we refer to a model of the economy focused on retaining the highest utility and value of products, components and materials at all times, through measures such as enhanced material efficiency, increased recycling, and extending product lifetimes (EUR-Lex, n.d.). The focus of the analysis is on the assessment of CE measures and policies applied to energy-intensive, basic material industrial sectors, specifically the production of steel, aluminium, and cement, which have significant potential for CE measures and for which alternative mitigation measures may be more limited.

However, the representation of such measures is often limited in IAM analysis, and therefore its potential is not typically fully explored (see section 2.1.3). To that end, we build on earlier model development activities in the DIAMOND project to improve the representation of such measures. This includes the extension to the Environmental Global Applied General Equilibrium (ENGAGE) model, a computable general equilibrium (CGE) model, that enables the assessment of CE policy impact on the wider economy, and three energy-focused IAMs that allow for a more detailed assessment of the balance of CE and non-CE measures in achieving decarbonisation targets. Deliverable 4.1 describes the development of all four models to enable a more detailed assessment of CE measures in the three selected industrial sectors, while Deliverables 3.7-3.9 provide detail on the wider development of the three energy-based IAMs used in this scenario analysis.

2.1.1 Prospects for circular economy measures in addressing climate goals

Direct industrial emissions are the second largest source of anthropogenic GHG emissions, accounting for around 24% of the global total in 2019. Basic materials sectors, on which this study focuses, account for the majority (over 60%) of direct and indirect CO_2 emissions, with marginal to no progress in reduction of carbon intensity of production observed in recent years (Bashmakov et al., 2022). This is a result of lack of progress on decarbonisation actions, e.g., a shift to hydrogen based DRI in steel or lower clinker cement, and increasing material intensity of the wider economy.

The IEA's Breakthrough Agenda Report (IEA, 2025) identifies several key challenges to scaling up mitigation measures across specific basic material sectors. For example, the steel sector has seen challenges to the delivery of investment on a pipeline of zero emission steel plants, with emission levels remaining unchanged in recent years. Despite some success in delivering the first CCS enabled cement plant, CO_2 emissions remain largely unchanged for this sector, and higher than in 2015.

Despite limited real world progress, scenario modelling studies, including those reviewed in the last IPCC assessment (AR6), do point towards the possibility of achieving net zero emissions across industrial sectors. This is based on a diversity of measures, including energy efficiency, use of clean energy (notably electricity), and circularity measures (Bashmakov et al., 2022). In a recent paper, Zanon-Zotin et al. (2026) undertook a review of the evidence on the mitigation potential of different CE strategies, using the R-Strategy framework (Potting et al.,

2017),[1] and the different modelling approaches used to assess such strategies. They highlighted a research focus on basic material sectors (particularly steel and cement), and the prevalent use of Material Flow Analysis (MFA) and Life Cycle Assessment (LCA) methods to determine potential. 'Reduce' strategies were most common in demand sectors and 'recycling' strategies in supply. Importantly, they found that the literature highlights the strong potential for CE measures to play a key role in GHG emission reduction, being complementary to other mitigations measures.

Wiedenhofer et al. (2025) undertook a review of 75 national and global studies that modelled CE measures, to assess mitigation potential of such measures. They found that combined CE strategies on their own see GHG mitigation potentials of 17% on average (range 0–91%) – but that their impact can be leveraged in combination with a broader portfolio of measures. A recent review of mitigation potential by the EEA (2026) put the potential emission reductions associated with CE at an average of around 33% globally (study range of 2-99%). The differences in averages result from different study samples (and size), leading to large differences in the average.

In terms of key papers assessing CE potential, Pauliuk et al. (2021) highlight the considerable material efficiency gains and associated emission reductions from such actions in residential buildings and passenger transport sectors, placing material efficiency as the third decarbonisation pillar alongside energy efficiency and low carbon energy supply. A more recent analysis by Pauliuk et al. (2024) focused on CE measures in the buildings sector, highlighting the potential role of reducing material inputs and increasing the use of wood as a substitute for more emissions-intensive materials to achieve a 44% reduction in cumulative emissions over the period 2020-50. Olsson et al. (2023) estimate that CE measures focusing on reducing clinker content of cement, enhancing structural design (requiring less cement), and lengthening lifetime of buildings have the potential to reduce GHG emissions by over 76%.

2.1.2 Circular economy in broader mitigation strategies

Given the recognition of their potential, CE measures have become a key part of resource and decarbonisation strategies in many regions. Notably, CE is considered a key element of the EU's move towards carbon neutrality, and wider objectives. The Commission states that –

> *The EU's transition to a circular economy is crucial for reducing pressure on natural resources, halting biodiversity loss, achieving climate neutrality by 2050, and building a more resilient and competitive Europe* (European Commission, n.d.).

This ambition is set out in the European Commission's Circular Economy Action Plan (European Commission, 2020), updating the previous 2015 plan. The document outlines the focus of European action on different product value chains, including areas that are relevant to basic materials, such as construction, which relies heavily on cement and steel. It is a key underpinning plan feeding into the European Green Deal, which sets out the agenda for sustainable growth in the European Union, including a commitment to carbon neutrality by 2050.[2]

This year, in 2026, the Circular Economy Act is due to be introduced. According to the Commission, the act will 'facilitate the free movement of 'circular' products, secondary raw materials and waste', and increase the supply of

[1] Aggregated into narrow (R1-2 e.g. reducing material input), slow (R3-7 e.g. extending product lifetime) and closed (R8-9 e.g. recycling materials) strategies.

[2] European Commission web page, The European Green Deal

recycled materials and stimulate demand for them.[3] This includes alignment with the Clean Industrial Deal, which also promotes circularity as a key part of its industrial strategy, with a target to double Europe's circular material use rate (CMUR), from 12%, to 24% by 2030 (European Commission, 2025). The CMUR is the share of all materials used in the economy that comes from recycled waste rather than newly extracted resources.

Action to promote circular economy thinking and measures are also being undertaken in other regions and at the international level, supported by organisations such as UNEP[4] and the OECD.[5]

2.1.3 Assessing CE measures using IAMs

It is evident from the IPCC AR6 report that CE measures are not well represented in IAMs, thereby under-representing their potential and potentially requiring more heavy lifting from other measures (Bashmakov et al., 2022). Pauliuk et al. (2017) highlighted this issue prior to the AR6 report. Based on a review of five major IAMs, they found limitations in the representation of industrial ecology (IE) in the models, and the need for linking to IE models, e.g. MFA, and better engagement between IAM and IE communities. This call for increased collaboration between communities was echoed by (Nikas et al., 2022).

These limitations are particularly important given the central role of IAMs in exploring global and regional mitigation strategies and the potential role of CE measures (section 2.1.1). Inadequate representation of such measures may increase reliance on more uncertain mitigation options such as carbon dioxide removal (CDR) through bioenergy with CCS (Edelenbosch et al., 2024); highlighting the importance of a balanced portfolio of mitigation strategies.

In recent years, there have been a range of developments to respond to this limitation in IAMs, including improving representation within IAMs e.g. (Ünlü et al., 2024), and connecting IAMs to MFA and LCA analyses e.g. (Boubault et al., 2019; Šimaitis et al., 2025). A review of the advances under this second strategy of linking is provided in section 4.7 of (Zanon-Zotin et al., 2026).

These enhancements have improved assessment of CE measure potential in IAMs, with the IMAGE model being most prominent. (Lu et al., 2024) link IMAGE to a global CGE model, GTEM, built using the GTAP database. They consider standalone climate and CE focused scenarios, before combining them in a third case. The implications of the analysis are explored for China, finding that reductions in materials of around 30% play an important role in achieving net-zero emissions. van Sluisveld et al. (2021) explore the decarbonisation of key heavy industries, including steel and cement using the IMAGE model, based on four scenarios. One of these, 'Circular economy', highlights the contribution of circularity measures, particularly secondary steel production, relative to fuel switching and other mitigation options. The paper focuses on overall strategies, with circularity being one of many measure typologies that could be considered. However, the paper does not isolate the specific contribution of circularity to mitigation. Sharmina et al. (2021) focus on decarbonisation of sectors that are challenging to abate, including industry. Using the IMAGE model, possible emission reductions are decomposed using a Kaya Identity approach. Circularity is identified as a key strategy for industrial sectors – although the extent to which such measures have been explicitly modelled is unclear.

[3] European Commission web page, Public consultation on Circular Economy Act

[4] UNEP website on their approach to circularity. https://www.unep.org/circularity

[5] OECD website on circular economy policies and country studies. https://www.oecd.org/en/topics/circular-economy-policies-and-country-studies.html

Speizer et al. (2023) explore steel decarbonisation strategies using the GCAM model, and highlight the strong contribution of increased scrap recycling and material efficiency, accounting for around 40% of the mitigation effort in 2050, relative to a 2050 reference case. Zhang et al. (2025) assess primary steel and emission reductions under China's carbon neutrality goal, using the GCAM model linked to an MFA model. They highlight the strong role of recycled scrap in reducing primary steel production, imports of iron ore, and associated emissions with this production pathway. Mastrucci et al. (2024) focus on circular strategies for the building sector in China using the IAM MESSAGEix and LCA model, estimating up to a 60% reduction in building materials in 2060 relative to a reference case, contributing significantly to GHG emission reductions.

2.1.4 Ongoing gaps in IAM representation of CE strategies

Despite recent improvements, notably through integration with MFA and LCA models, IAMs still face limitations in representing the potential contribution of CE measures. Three recent review papers provide an up-to-date overview of how IAMs represent CE measures, with recommendations that inform and justify the approach adopted in this study (Magalar et al., 2026; Wiedenhofer et al., 2025; Zanon-Zotin et al., 2026).

Zanon-Zotin et al. (2026) highlight that a constraint of global CGE and process-based IAMs is that they typically do not capture material-flow dynamics and stocks, which makes it difficult to simulate CE measures. They therefore highlight the use of a linking approach as a key modelling approach to overcome this. Four key gaps are highlighted from the review: (i) limited representation of specific R-Strategies (e.g. refuse and slow strategies (e.g. extending lifetime)); (ii) different CE strategies being assessed individually, missing insights around interactions; (iii) limited representation of dynamics including rebound effects, spillovers, and co-benefits; and (iv) limited integration of CE-focused and broader climate mitigation approaches.

Wiedenhofer et al. (2025) highlight that there is a much stronger focus on national assessment of CE measures compared to global studies. Based on their review, they identify three future research needs of relevance to global assessments. First, this includes more granular representation of material flows and potential for circularity in climate assessments, requiring linking between LCA/MFA with IAMs that capture wider socioeconomic dimensions. Second, they highlight the need for improved data to better understand the potential of CE measures e.g. rates of recovery for recycling, costs of product maintenance, consumer behaviour etc. Third, they identify a need for better representation of transport and trade.

In their review of how IAMs represent CE measures, Magalar et al., (2026) identify four issues requiring further consideration. These include: i) limited focus on slowing strategies, with narrowing and closing strategies dominating (echoing (Zanon-Zotin et al., 2026)); ii) a lack of granularity of material flows and measures to model CE options; iii) limitation of representing full supply chain effects and interactions between CE strategies; and iv) a limited ability to simulate more detailed policy measures and packages.

Addressing some of these gaps, this study adopts the following –

- A process of improving representation of the granularity of key sectors subject to CE measures in a set of IAMs, as detailed in DIAMOND deliverable 4.1.
- A linking strategy between a global energy system model, OMNIA, and a global CGE model ENGAGE. This allows for more detailed simulation of policy packages in ENGAGE, enabling spillover and interactions (including rebound effects) between sectors – and implications on commodity demand. ENGAGE also enables insights on trade of commodities, and an understanding of where actions take place.
- A focus on demand (narrowing strategy, reducing material inputs) and supply (closed strategy, increased recycling) at the same time with other mitigation measures in IAMs, to understand synergies and

contribution to mitigation targets.

2.1.5 Focus of this study

The objective of this study, therefore, is to assess the role that circular economy measures have within the portfolio of mitigation measures needed to decarbonise key industrial sectors, namely steel, aluminium and cement, and their contribution to meeting broader EU and global climate objectives. A stronger role could potentially reduce the costs of mitigation (in sectors with high costs of mitigation) and reduce reliance on more uncertain technology options such as CCS. Furthermore, there may also be wider economic benefits from reducing the throughput of different materials.

Two research questions emerge that support the above objective, which have been tested in WP2 activities (see Deliverable 2.5 for additional details) with a range of stakeholders for saliency and relevance. These are:

1. What is the contribution of CE policy packages in delivering regional and global climate goals?
2. What are the broader impacts of these CE policies across different regions and sectors?

Question 1 first explores how implementation of CE policy package helps deliver climate policy targets, and the balance with other mitigation measures. This includes through implementation both across Europe and in other regions of the world. Question 2 further explores the distributional implications spatially and across sectors, resulting from implementation of policy packages in different geographies. As described in the next section, we undertake a scenario modelling approach, using four separate models - the coupled OMNIA-ENGAGE framework together with comparators OPEN-PROM (global IAM) and GCAM-Europe (European IAM) - to gain insights both on the economy wide impacts of CE measures, and their role in mitigation of key industrial sectors and the wider energy system.

The structure of this study report in section 2 is as follows; we first consider our approach to the study in section 2.2, describing the overarching approach, models used, and scenario design and implementation. Results from the modelling are then presented in section 2.3, with a discussion on policy implementation and conclusions following in section 2.4. References are listed in section 2.5.

2.2 Study design

2.2.1 Overarching approach

As highlighted earlier (section 2.1.3), many IAM analyses inadequately capture the potential for CE measures or do so in a limited or partial way. This is due to model structural issues, lack of representation in scenarios, or an inability to simulate the policy impacts. On structure, the suite of models used in this study was first improved in terms of industrial sector representation (as described in DIAMOND Deliverable 4.1).[6] These models are briefly described in the next section (2.2.2). The application of the models was guided by a scenario protocol that was designed to specifically assess the role CE measures could play in industrial decarbonisation, as described in section 2.2.3. The implementation of the protocol in the models is then described in section 2.2.4. To simulate policy impacts, the coupling of ENGAGE with OMNIA was critical for the ability to represent specific policies more

[6] The published models for OMNIA, GCAM-Europe, and OPEN-PROM, all developed under DIAMOND, can be found here. The further development of this set of models and ENGAGE, for use in this study, is described in detail in DIAMOND deliverable 4.1.

fully.

2.2.2 Overview of models

The four models used in this study include:

- **ENGAGE**. A global CGE model, developed specifically for the assessment of circularity measures, with enhancement in DIAMOND to improve metals and cement sector representation. The use of this model is crucial for the simulation of CE policy measures and resulting commodity demand, trade and wider economic effects.
- **OMNIA**. A new global energy system model based on the TIMES framework, developed under DIAMOND. This model is used to represent the detailed technology options for industrial sector decarbonisation, and how climate action in these sectors impacted on overall system costs and contribution to mitigation across sectors. The linking with OMNIA is described in this section below.
- **GCAM-Europe**. A new version of the GCAM model specifically built to provide a more granular representation of the European energy system at a country resolution (Sampedro et al., 2026). This includes representation of all EU member states and other non-EU European countries, while significantly improving the sectoral granularity, data quality, and overall model coherence on the European continent. See DIAMOND deliverable 3.8 for more details about the model. For the purpose of this study, GCAM-Europe version 8.7.3 has been used.
- **OPEN-PROM** a modular, open-source IAM and global energy-system model, based on the model PROMETHEUS (Fragkos et al., 2015).

2.2.2.1 ENGAGE

The ENGAGE (Environmental Global Applied General Equilibrium) model is a dynamic computable general equilibrium (CGE) framework designed to analyse the economic, environmental, and sectoral impacts of policies related to resource efficiency and the circular economy. As part of the project, the model's scope has been extended to improve its representation of circularity in the metals and cement sectors, building on previous research efforts (Nechifor et al., 2020; Winning et al., 2017). The model provides a detailed representation of flows in the economy emphasising the global interplay of resources, trade, and policy interventions. Hence, it is well suited to addressing the research questions of this study.

The enhancements made to ENGAGE both to its geographic and sectoral structure have been done to align with OMNIA, as these two models are linked. For example, the geographical representation of the global economy has been changed, increasing from 19 regions to the same 28 regions used in OMNIA. Key datasets related to sectoral calibration e.g. steel production / capacity, clinker production, are also aligned across the models. Further information on the extensions to ENGAGE can be found in Deliverable 4.1.

2.2.2.2 OMNIA

The OMNIA (Open-source MuNdus Integrated Assessment) model is an open-access global Integrated Assessment Model (IAM) based on the TIMES framework.[7] It represents the global energy system, including all

[7] The TIMES framework, which underpins this model, is described in detailed in Loulou et al., (2016). It is a modelling framework

energy sectors, from energy resources, their transformation into energy commodities (petroleum products, electricity, hydrogen, biofuels etc.), to consumption in end use sectors (industry, transport, buildings, and agriculture). Such a system is represented across 28 regions.

The model is technology rich, with each sector represented by current energy producing and consuming technology stocks, including power plants, blast furnaces, vehicles, and buildings, among others. This representation of the system is calibrated to represent the energy production and use (flows) in the base year, 2019, and associated GHG emissions. Exogenous projections of future energy service demands (such as mobility, cooling, industrial output) allow for an assessment of new technology requirements and investment out to 2100, and their associated GHG emissions. The emissions output allows for assessment of the energy system's contribution to total GHGs, and different approaches to mitigation. Energy service demands across 28 geographical regions can be met by both domestic resources and traded commodities. Regions are connected via pipelines and / or shipping routes, enabling the trade flow of the main energy commodities, including fossil fuels, bioenergy, and hydrogen-based fuels.

In view of the application to the question of industrial circular economy, OMNIA was designed with additional detail across the three industrial sectors of interest – steel, aluminium and cement. This meant explicit representation of key decarbonisation options, and a sector structure that allowed for assessment of CE measures e.g. secondary production based on scrap, clinker contents of cement etc. Further information on the structure of these sectors can be found in Deliverables 3.9 (OMNIA) and 4.1.

2.2.2.3 OMNIA-ENGAGE linkage

The OMNIA and ENGAGE models have been linked to overcome key problems of representing circular economy measures. OMNIA, as a global energy system model, provides a detailed representation of the energy system and the options to decarbonise steel, aluminium and cement. However, it cannot represent CE policy measures and their impact on individual economic sectors which are highly interconnected through integrated supply chains. Such detail is needed to understand how measures impact the production of basic materials.

For example, policies that incentivise changes in construction practice impact supply and use of cement and steel, more efficient use of steel in vehicle manufacture reduces demand, while increased demand for recycled metal has further implications for upstream production. ENGAGE, as a CGE model built using input-output tables, has a more granular representation of the industrial supply chains, and the dependencies between sectors, to assess how measures that target sectoral demand for industrial commodities will impact on the production of those commodities. However, its representation of industrial production technologies, energy use and emissions is much more limited, which is a strength of OMNIA.

Hence linking these models to better assess the role of CE measures is a useful modelling strategy. The basic linkage approach is provided below, in Figure 2.1.

developed and maintained by the Energy Technology Systems Analysis Programme (ETSAP) community, a Collaboration Programmes of the International Energy Agency (IEA). It has been used extensively across many countries and also provides the basis for the TIAM family of global integrated assessment models (e.g. Pye et al., 2025; Welsby et al., 2021). The model paradigm can be characterised as partial equilibrium, optimisation-based, with an objective of welfare maximisation over the model time horizon.

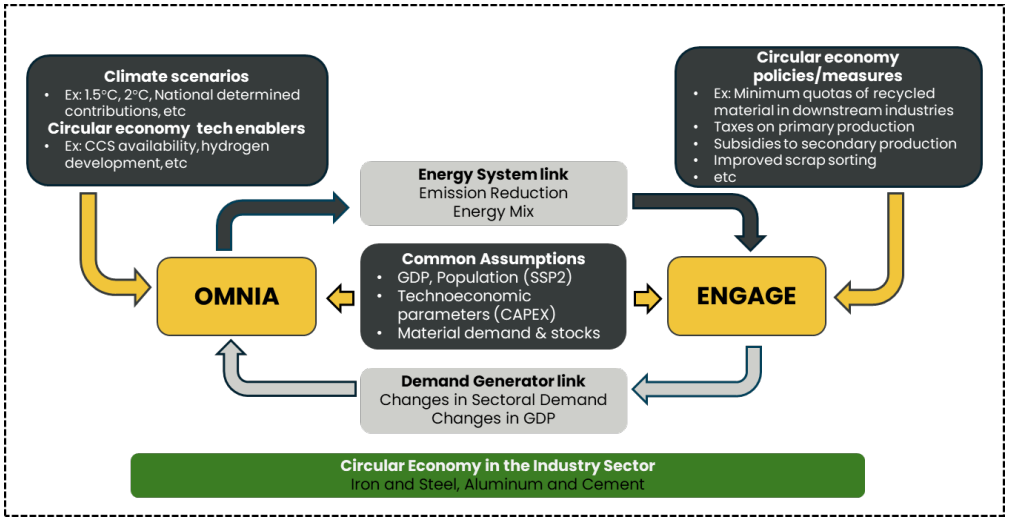

Figure 2.1. The conceptual linkage and information flow between ENGAGE and OMNIA

To ensure a robust linkage, improvements to sectoral representation are harmonised across both models, including the underlying data on production profiles for the three sectors of interest. This includes ensuring the same production capacities, and shares of primary vs secondary production across geographical regions.

In the bidirectional soft-linking approach, emission reduction pathways are first passed from OMNIA to ENGAGE. ENGAGE then configures an economy-wide equilibrium for a case with no CE policies implemented (see section 2.2.3), consistent with the GHG emissions trajectory modelled in OMNIA. Both models also use harmonised projections of key drivers, including commodity production (cement, steel and aluminium), population and GDP. ENGAGE is now in a position to start simulating CE policy measures, and determining changes to sectoral use of the basic materials of interest, with implications for downstream and upstream production, and wider economic impacts. After each policy simulation (defined by scenarios described in the next section), regional commodity production values (including shares of primary and secondary production for steel and aluminium) are passed back to OMNIA to explore implications on emissions and production technology investment and use.

At this stage, there is no further iteration between OMNIA and ENGAGE, as the emission profiles from OMNIA across the regions do not change as a result of the CE policy implementation. Rather, it is the allocation of mitigation effort within industry and between industry and other sectors where adjustments are seen.

2.2.2.4 GCAM-Europe

GCAM-Europe is a regionalised version of the Global Change Analysis Model (GCAM), a recursive-dynamic, partial-equilibrium integrated assessment model that explores interactions among energy, the economy, land use, water and climate under alternative socioeconomic and policy scenarios (Sampedro et al., 2026). Developed within DIAMOND, it replaces the five broad European regions of the global model with country-level representations covering all 27 EU Member States and other European countries, while retaining links to the wider global economy. The model operates at five-year intervals to 2100, with European calibration strengthened through Eurostat energy balances, country-specific demographic projections and more detailed sectoral datasets. Enhancements to the electricity system include interconnected grid regions, transmission-constrained cross-regional trade, four intra-annual load segments and electricity storage, allowing a more differentiated assessment of renewable integration and system flexibility. The building sector distinguishes space heating, water heating, cooking and other residential end uses, with explicit representation of heat-pump technologies and household demand by income decile. Transport calibration has also been refined using JRC-IDEES data, alongside the integration of survey-informed trajectories for electric-vehicle adoption. Additional improvements cover intra-European commodity trade,

cement-sector data and the representation of household consumption patterns. These developments improve the model's ability to examine geographically differentiated decarbonisation pathways, sectoral transformations and the implications of European climate and energy policies, while accounting for interactions with international markets. This study uses GCAM-Europe version 8.7.3; further details on the model's development and structure are provided in DIAMOND Deliverable 3.8.

2.2.2.5 OPEN-PROM

OPEN-PROM (Open PROMETHEUS) is an open-source, simulation-based Integrated Assessment Model (IAM) developed to analyse the evolution of the global energy system under alternative socioeconomic, technological and climate policy assumptions. The model is implemented in GAMS and follows a recursive-dynamic approach, simulating energy system developments in annual time steps up to 2100. It covers 39 countries and regions, including individual EU Member States and major global economies. It provides a detailed representation of energy demand, energy supply, technology deployment, fuel consumption, energy prices and greenhouse gas emissions. OPEN-PROM represents the main energy-consuming sectors, including industry, residential and commercial buildings, transport and non-energy uses, as well as energy supply technologies for electricity, hydrogen, heat and other fuels. Socioeconomic and sector-specific variables drive energy demand, including GDP, population, industrial activity, energy prices, and technological developments. The model first determines useful energy requirements and subsequently calculates final energy consumption based on the available technologies and their conversion efficiencies.

Technology deployment is simulated through a gap-and-substitution mechanism that accounts for changes in energy service demand, the retirement of existing equipment and the allocation of new investments among competing technologies. Technology shares evolve according to relative costs, fuel prices, conversion efficiencies, technology maturity and climate policy measures, including carbon pricing. This framework captures the gradual replacement of existing technologies and the penetration of low-carbon alternatives, while maintaining consistency between energy demand, fuel supply, energy prices and emissions.

Industrial sector representation and application in this study

The industrial sector in OPEN-PROM is represented through energy-consuming technologies associated with different fuels, including coal, oil, natural gas, electricity, biomass and hydrogen. Industrial energy demand is differentiated by subsector, while the evolution of the energy mix depends on changes in useful energy requirements, technology efficiencies, relative energy costs and the substitution between fuel-based technologies. The model therefore captures industrial decarbonisation primarily through fuel switching, electrification, energy-efficiency improvements, and changes in the carbon intensity of energy carriers.

OPEN-PROM is currently developing a more detailed representation of industrial production processes and low-carbon technologies in other research activities, including the Horizon Europe TRANSIENCE project[8]. For the present deliverable, however, the analysis relies on the fuel-based technology representation described above.

The analysis focuses on the iron and steel sector, where electrification can serve as a proxy for estimating the

[8] TRANSIENCE (TRANSItioning towards an Efficient, carbon-Neutral Circular European industry) is a Horizon Europe project (2024–2027) developing an open-source modelling framework to assess pathways towards a circular and climate-neutral European industry, integrating material efficiency and circularity measures into energy and climate models. Further details are available at https://www.transience.eu/

potential contribution of secondary steel production. In particular, the share of electricity in the sector's energy mix indicates the potential penetration of electric arc furnace (EAF) steelmaking, the main production route for secondary steel using recycled scrap. By examining electrification levels under different scenarios, the analysis derives an indicative estimate of secondary steel production and its potential contribution to circular economy strategies.

This approach provides a simplified representation of the relationship between electrification and secondary steel production, as electricity consumption may also increase through other industrial technologies and production routes. Nevertheless, it provides a basis for exploring the implications of increased material circularity for industrial energy demand, fuel substitution and associated CO_2 emissions within the OPEN-PROM modelling framework.

DIAMOND Deliverable D3.7, the OPEN-PROM final version, and the documentation provide further details on the model structure, sectoral representation, and technology substitution mechanisms.

2.2.3 Scenario design

The scenario design incorporates three dimensions that allow for insights on the role of CE measures: i) climate policy ambition, ii) circular economy policy ambition, and iii) regional implementation. On i), to assess the role for CE measures, it is insightful to explore how different climate ambition levels drive different levels of action. For ii), on CE ambition, it is interesting to explore how different levels of CE policy impact on the range of mitigation actions seen across different countries and regions. Finally for iii), we explore how different regional uptake and implementation of such CE policy packages will impact the role such measures have on mitigation across sectors. This reflects differences in levels of policy coordination internationally versus more unilateral actions.

2.2.3.1 Climate policy ambition

There are two levels of EU and global climate policy ambition that are considered, derived from DIAMOND's Baseline Scenario Protocol (see D5.2 for more details).

- **NDC.** This ambition level is determined by Nationally Determined Contributions (NDCs) by country in 2030 and 2035, with unconditional targets preferred and conditional goals only used where the former is not available. Post 2030/35, the level of ambition at the regional level is set by extrapolating the derived carbon prices (from the NDC target) based on the change in GDP per capita. This approach follows the standard methodology for the extrapolation of emissions limits after an emissions target has been reached within the DIAMOND project.
- **NDC and long-term targets (NDC+LTT).** In this case NDCs are modelled in 2030 and, for those countries which have them, 2035. Beyond 2035, and if a country does not have a 2035 target, where a country has an LTT then we follow the standard DIAMOND protocol and linearly interpolate between their available targets. However, if a country does not have an NDC in 2035 or an LTT, then we assume the emissions share that country makes up of the region it is in remains the same as in 2030 and use the respective model's no-climate-policy reference case to extrapolate their emissions limits.

2.2.3.2 Circular economy policy ambition

Circular economy policies comprise of two categories:

- **Production-focused.** These are policies that target reductions in material requirements in production of metals and cement, based on a 'closed' CE strategy that focuses on increased recycling and less primary production. This includes increasing the share of secondary production for steel and aluminium and

reducing the clinker-to-cement ratio for cement. Targets values are set for 2030 and 2050 and represent the minimum levels to be achieved under each scenario (see Table 2.1).

- **Consumption-focused.** These are policies that reduce the demand for commodities as a result of improved material efficiency or lower material demand, based on so-called 'narrow' or 'slow' CE strategies. This includes measures that reduce the material input into products or infrastructure (narrow), or that extend product lifetime, reducing inputs due to manufacture of fewer new products (slow). Implications of policies on consumption are listed in Table 2.1 below.

The selection of targets / policies and ambition levels are listed below in Table 2.1.

Table 2.1. Circular economy policy packages for medium and high ambition levels

Sector	Measure type	Measure	Medium ambition			High ambition			Ref.
			2030	2040	2050	2030	2040	2050	
Steel	Production	Secondary production share (%)	41%		50%	52%		65%	[1]
	Consumption	Change in total production required	-1.5%		-3.1%	-2.3%		-4.5%	[2]
Aluminium	Production	Secondary production share (%)	45%		57%	50%		67%	[3]
	Consumption	Change in total production required	-0.10%	-3.9%	-10.3%	-0.2%	-6.3%	-16.7%	[4]
Cement	Production	Clinker-to-cement ratio	0.67		0.61	0.65		0.57	[5]
	Consumption	Change in total production required	-10.4%		-20.3%	-17.3%		-28.9%	[6]

[1] Based on the ambitious 2050 circularity and decarbonization goals (Domenech et al., Forthcoming)
[2] Based on reductions in construction due to lower floorspace requirement (Grubler et al., 2018), vehicle mass reductions (Advanced Propulsion Centre UK, 2024), and primary steel reduction in passenger cars (Material Economics, n.d.)
[3] Based on the moderate lifetime-extension scenario (Ma et al., 2026)
[4] Sourced from (Ma et al., 2026)
[5] Sourced from (IEA, 2023)
[6] Reduction in floorspace (Grubler et al., 2018) combined with reduction in cement input per unit of floorspace (Cemburea, 2024)

For OMNIA-ENGAGE, a two-step process was implemented, based on the linking approach. First the consumption measures were introduced in ENGAGE, and the production targets were achieved through the introduction of a range of additional policies such as subsides/taxes and higher recycling rates. The impacts of the simulation of the different policy packages, in combination with different climate targets (2.2.3.1) and regional implementation (2.2.3.3), allowed for a wider set of insights on economic impacts, including rebound effects. The resulting outputs from ENGAGE were then used to revise the corresponding inputs in OMNIA (see Table 2.2). For OPEN-PROM and GCAM-Europe, the target values in Table 2.1 were entered directly in the respective models (without having been simulated first in ENGAGE). This alternative approach highlights the contrast between the linkage of CGE model with IAMs, versus IAMs not linked to a CGE model.

The **medium ambition** CE policy package introduces incremental measures focused on improving recycling and resource efficiency. In the steel sector, this means moderate scrap recycling targets, limited incentives for EAF adoption and basic sorting improvements. For aluminium, it includes moderate scrap recycling targets and limited support for secondary aluminium. In cement, it encourages clinker substitution and efficiency improvements along the supply chain.

The **high ambition** CE policy package applies stronger measures across all sectors and integrates them with climate policies, aligning with net zero emissions targets. For steel, this includes mandatory high-quality scrap

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standards, strict targets on EAF production, taxes on primary production, subsidies on secondary production, mandatory secondary input content, and high scrap recycling targets. For aluminium, it sets strict targets on secondary input content, and imposes taxes on primary production, subsidies on secondary production, and high scrap recycling rates. In cement, it mandates clinker substitution ratios, efficiency improvements along the cement and concrete supply chain, and enforces circular design standards.

Table 2.2. Circular economy policy measures after ENGAGE simulations for use in OMNIA
Values for the NDC scenario is in the upper table, and for NDC+LTT, in the lower table. Note that these are values for the changes in the regions implementing policies. Note that secondary production shares for aluminium and clinker-to-cement ratios remain unchanged from Table 2.1.

Sector	Measure	EU implementation				EU + partner implementation			
		Medium ambition		High ambition		Medium ambition		High ambition	
NDC		2030	2050	2030	2050	2030	2050	2030	2050
Steel	Secondary production share (%)	61%	91%	61%	91%	43%	55%	44%	66%
	Change in total production	0.2%	1.1%	0.2%	1.1%	-5.2%	-11.9%	-5.8%	-24.0%
Aluminium	Secondary production share (%)								
	Change in total production	-2.7%	-9.8%	-3.7%	-12.0%	-3.7%	-7.4%	-5.3%	-14.9%
Cement	Clinker-to-cement ratio								
	Change in total production	-3.9%	-10.5%	-6.0%	-15.7%	-5.4%	-8.0%	-8.0%	-17.9%

Sector	Measure	EU implementation				EU + partner implementation			
		Medium ambition		High ambition		Medium ambition		High ambition	
NDC+LTT		2030	2050	2030	2050	2030	2050	2030	2050
Steel	Secondary production share (%)	61%	91%	61%	91%	43%	55%	44%	65%
	Change in total production	0.2%	1.1%	0.2%	1.1%	-5.2%	-11.6%	-5.8%	-23.8%
Aluminium	Secondary production share (%)								
	Change in total production	-2.7%	-9.8%	-3.7%	-11.9%	-3.7%	-7.3%	-5.3%	-14.4%
Cement	Clinker-to-cement ratio								
	Change in total production	-3.9%	-10.5%	-6.0	-15.6	-5.4%	-8.2%	-8.0%	-18.1%

The secondary share of steel production in the EU reaches 91% by 2050 in the medium and high ambition scenarios because steel demand is projected to fall to 57% of its 2019 level, while scrap availability increases by more than 30%. Given that over 40% of EU steel production already comes from secondary sources, the available scrap is sufficient to meet most future demand, making a 91% secondary production

share achievable.
Changes in total production are driven by the consumption measures and production targets introduced in ENGAGE.

2.2.3.3 Regional policy coverage

The third scenario dimension is the region of focus for where the policy package will be introduced. The reason for differentiating regional implementation is to understand the implications of a future where EU policy is undertaken unilaterally, to assess its contribution to EU decarbonisation and for the global modelling analysis, its implications for the rest of the world. This is then contrasted with a more global implementation of policies in different regions, exploring a more internationally coordinated approach. The implementation by region of circular economy measures is shown in Table 2.3.

Table 2.3. Detailed list of two regional implementation approaches by model region

OMNIA regions	Description	EU only	EU + International partners
AFE	Eastern Africa		
AFN	Northern Africa		
AFW	Western Africa		
AFZ	Southern Africa		
ANZ	Australia and New Zealand		Yes
ASC	Central Asia		
ASE	Southeast Asia		
ASO	South Asia		
BRA	Brazil		Yes
CAN	Canada		Yes
CHL	Chile		Yes
CHN	China		Yes
ENE	Eastern Europe Non-EU		Yes
ENW	Western Europe Non-EU		Yes
EUE	Eastern Europe Union	Yes	Yes
EUM	Mediterranean Europe Union	Yes	Yes
EUW	Western Europe Union	Yes	Yes
IDN	Indonesia, Philippines & Vietnam		Yes
IND	India		Yes
JPN	Japan		Yes
LAM	Latin America		
MDA	Mediterranean Asia		
MEA	Middle East (Gulf States)		
MEX	Mexico		Yes
NIG	Nigeria		
RUS	Russian Federation		Yes
SKT	South Korea & Taiwan		Yes
USA	United States		Yes

2.2.4 Scenario implementation

The scenarios assessed combine the two levels of climate policy ambition, two circular economy policy packages and two regional implementation variants. The full set of scenarios and their corresponding settings are presented below in Table 2.4.

Table 2.4. Detailed list of scenarios

No.	Scenario name	Climate ambition	Circular economy package	Regional implementation
1	NDC noCE	NDC only	No policy	--
2	NDC M-EU	NDC only	Medium	EU only
3	NDC H-EU	NDC only	High	EU only
4*	NDC M-EU+	NDC only	Medium	EU + International partners
5*	NDC H-EU+	NDC only	High	EU + International partners
6	NDC+LTT noCE	NDC and LTT	No policy	--
7	NDC+LTT M-EU	NDC and LTT	Medium	EU only
8	NDC+LTT H-EU	NDC and LTT	High	EU only
9*	NDC+LTT M-EU+	NDC and LTT	Medium	EU + International partners
10*	NDC+LTT H-EU+	NDC and LTT	High	EU + International partners

* These scenarios are only modelled in OMNIA-ENGAGE and OPEN-PROM

Before running, all models were calibrated to common baseline pathways to 2050, for the noCE cases. This was done by implementing the same climate targets, and harmonisation of regional GDP, population, primary and secondary steel and aluminium production, availability of steel and aluminium scrap, and cement production.[9]

2.3 Results

This results section includes a description of the model outputs without CE policies included (2.3.1), providing an assessment of a system with limited CE measure uptake, and a subsection that considers the role that CE policies can play in complementing other mitigation measures, including variations based on geography of implementation and level of CE ambition (2.3.2).

2.3.1 No additional circular economy policy (noCE) scenarios

Prior to assessing the impact of circular economy (CE) measures, we first consider the two different climate ambition policy settings, NDC and NDC+LTT, without additional CE policies, to provide scenario counterfactuals from which to explore CE policy implications. Results are shown for OMNIA-ENGAGE only, in view of similar noCE cases produced by OPEN-PROM and GCAM-Europe that are closely harmonised.

2.3.1.1 Production of basic materials

We start with the production of basic materials across the three sectors of focus. From a circularity perspective, we are interested in how policies can both reduce overall production but also increase the share of secondary production (for metals) and reduce clinker content of cement. The global production outlooks without CE policies are shown below in Figure 2.2.

Cement production decreases from 4,200 Mt yr^{-1} in 2019 (the model base year) to 3,660 Mt yr^{-1} in 2050, approximately a 13% reduction over the time period, largely due to a reduction in demand in China (Figure 2.3). Clinker production, a key input to cement, reduces by a similar rate, around 14%. The difference between cement and clinker, the clinker-to-cement ratio, therefore, only reduces by around 1%, to around 0.71 (tonnes of clinker

[9] All baseline assumptions are available on GitHub.

per tonne of cement).

Both metals sectors see an overall increase in production by 2050, 25% for steel and 41% for aluminium, relative to 2019. However, the composition of production changes over time, with an increasing share of secondary production, due to increased stocks of steel and aluminium stocks and more recycling across the economy. For steel, the secondary share rises from 20% to 36%, covering the observed growth in steel output. Similarly, aluminium's secondary share increases from 34% to 49%. Both metals sectors show increasing circularity over time in the noCE cases, prior to the incorporation of additional CE policy measures, due to the lower costs of secondary production, and it being a cleaner production pathway under climate targets. The NDC and NDC+LTT noCE scenarios are both capped at the same global secondary production shares, providing a basis to assess the implications of additional circularity policies. Overall production output in these noCE cases is not impacted due to the absence of material efficiency policies, and no demand response to changing prices.

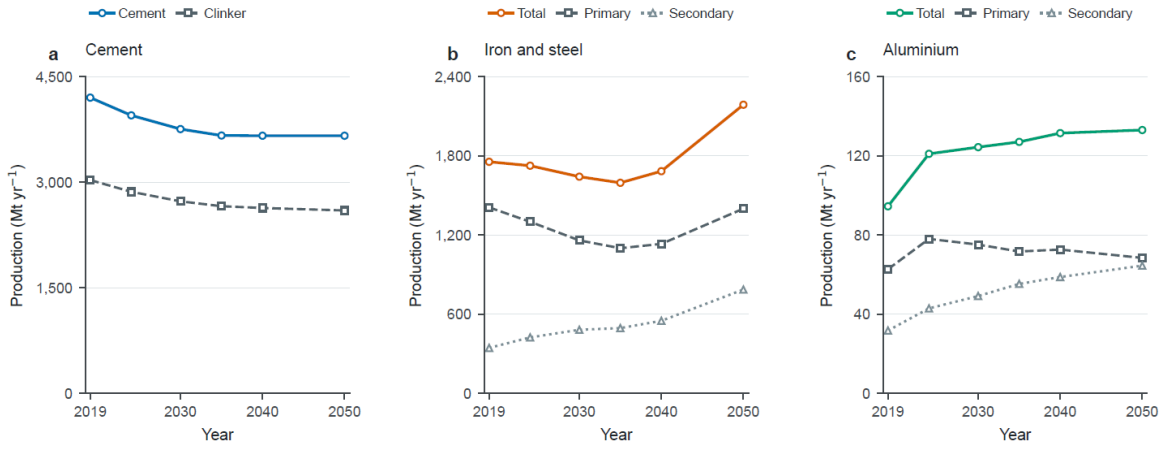

Figure 2.2. Total global basic material production, secondary production and clinker production under noCE cases in OMNIA-ENGAGE, 2019-50.

Note that there is no difference between production assumptions in the noCE cases between NDC and NDC+LTT scenarios. Other models contributing to this study are harmonised to represent the same production outlooks.

Changes in total production can be further disaggregated by region. Figure 2.3 shows this change between 2019 to 2050, again for all three basic materials, across 12 distinct producer country groupings that account for over 85% (cement) to 95% (metals) of global output; residual production from 'other model regions' is shown at the bottom of the figure. For cement, as noted earlier, the largest change is for China, where production more than halves by 2050, resulting in a global reduction (Figure 2.2). Conversely other regions see large increases, notably India, South Asia and other regions in Africa. European and USA production remains relatively stable.

Steel sees a more pronounced shift between regions, with emerging economies such as India, Brazil and other parts of developing Asia experiencing large increases. China remains the largest producer, even in 2050, despite seeing a decline in absolute production levels. This reflects its hugely dominant position today, capacity which will continue to be used to meet slowing domestic demand and exports. OECD economies all see declines in production over the period. The aluminium sector experiences a similar pattern although different current geographical capacity shapes who remains as the key producers, even in the long term. Exceptions are Other Asia-Pacific and Indonesia Group that become much more prominent.

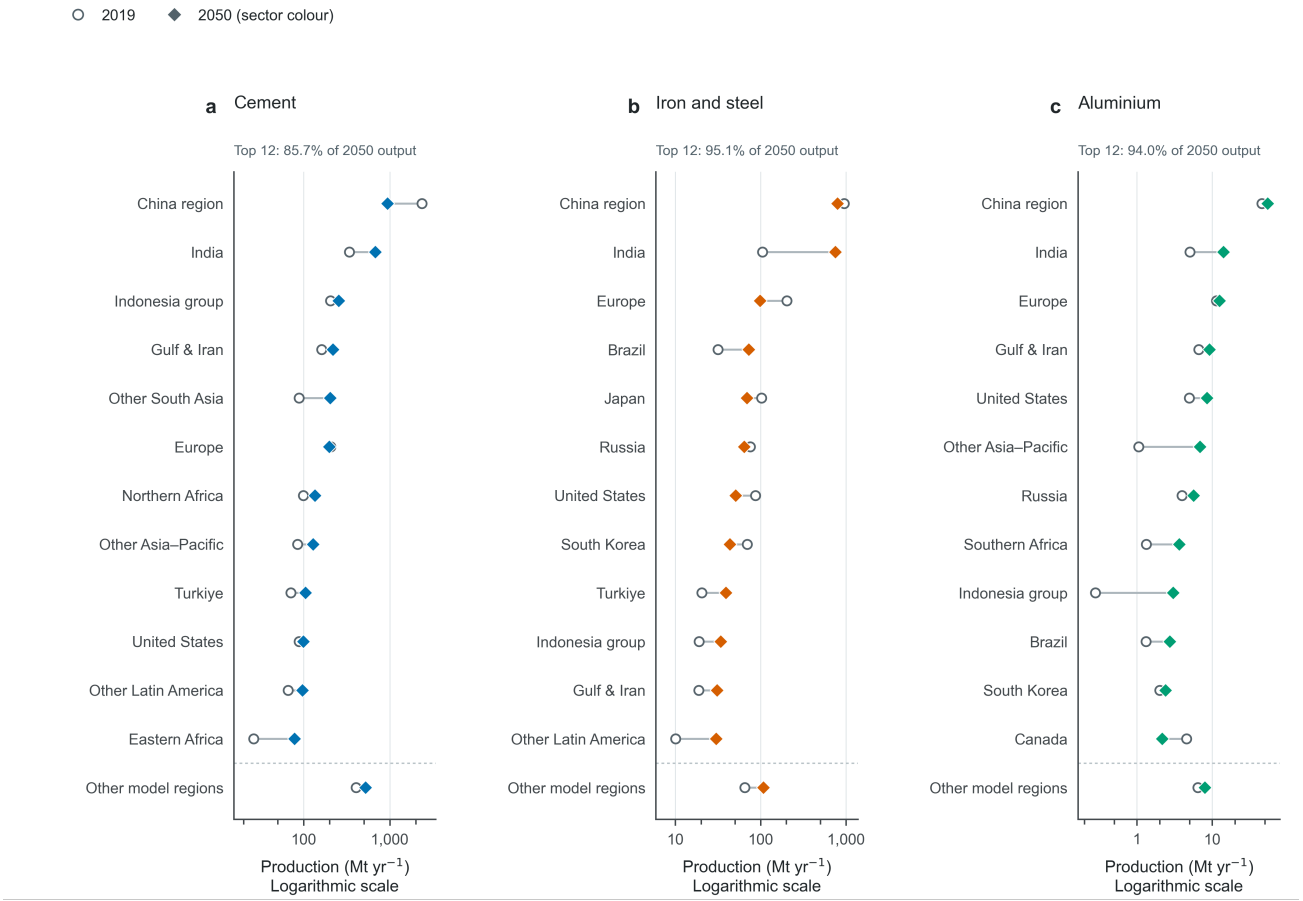

Figure 2.3. Basic material production by region under noCE cases, for 2019 vs 2050 in OMNIA-ENGAGE. Note that the same regional production is assumed for both the NDC and NDC+LTT cases. The Indonesia group includes Indonesia, Philippines, and VietNam.

2.3.1.2 Energy consumption and energy intensity of basic material production

Basic material sectors are large consumers of energy. It is therefore instructive to assess energy use under the different scenarios. Both metals sectors in both noCE cases see an overall decline in energy consumption, despite overall increases in production (Figure 2.4, upper panel); for aluminium this decrease in energy demand follows a near term increase in production. These energy demand reductions are in large part driven by the increase in secondary production that both sectors experience, as shown by the falling energy intensities of production (Figure 2.4, lower panel).

The limited differentiation between noCE cases for aluminium, despite higher carbon prices in NDC+LTT compared to NDC, is due to: i) the Hall–Héroult smelting process, powered by electricity, underpinning all primary production routes and accounting for the vast majority of sector energy consumption and ii) secondary production being constrained to follow the noCE paradigm. Steel does see a difference in final energy and energy intensity between noCE cases, with divergence after 2030. This difference is principally driven by a greater electrification of primary production in the NDC+LTT scenario relative to the NDC case because higher carbon prices in the former make molten oxide electrolysis cost effective. The NDC future instead relies on coal direct reduction while both scenarios see a similar role for natural gas direct reduction in the global steel production mix.

The cement sector sees a decline that matches the rate of production decline. A faster rate of reduction than that seen for production is not observed, due to no improvements in energy intensity of production. This is because compared with the NDC case the NDC+LTT future switches to more biomass fuelling cement production which,

while low carbon, offers comparable energy intensity to coal. Furthermore, the economics of shifting to more efficient kiln technologies do not make sense given the high CAPEX requirement for small efficiency gains.

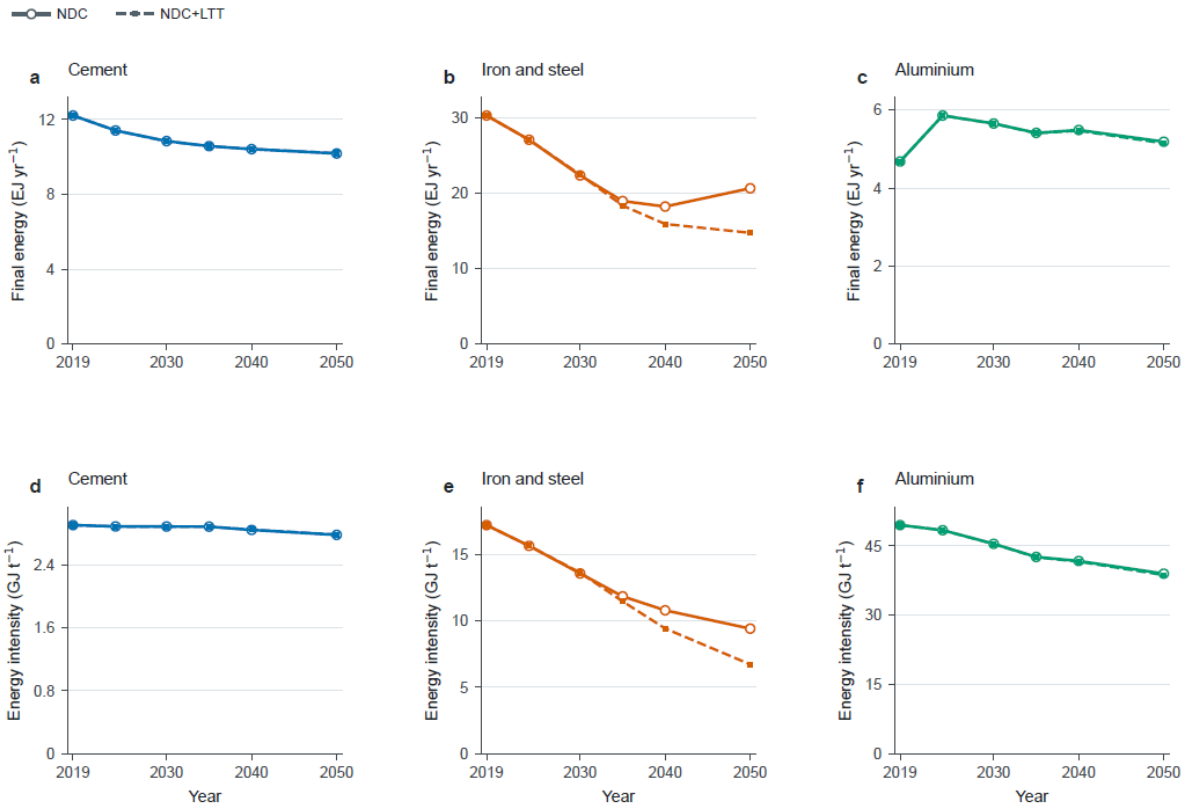

Figure 2.4. Energy consumption and intensity of global production of basic material sectors under noCE cases from OMNIA-ENGAGE, 2019-50.
a-c: global final energy consumption; d-f: energy intensity, the ratio of final energy to material production.

2.3.1.3 GHG emissions from basic material production

Finally, we assess the emissions footprint of the three sectors in the noCE cases using a variety of metrics. Cement emissions decrease from 2.5 Gt CO_2e yr^{-1} in 2019 to 1.8 Gt CO_2e yr^{-1} under NDC and 1.7 CO_2e yr^{-1} under NDC+LTT in 2050 (Figure 2.5a). In large part this is due to falling production but also mitigation through a switch to biomass fuelling and some modest deployment of CCS technology (Figure 2.5d). In part this highlights the challenge of addressing emissions from this sector, as shown by the limited GHG intensity improvement over time (Figure 2.5c), and the potentially important role for CE policies. The limited mitigation progress in the sector leads to an increasing contribution from cement to overall industrial GHG emissions (Figure 2.5b).

The steel sector sees the largest reductions in emissions in the noCE cases, with reductions from 2.7 Gt CO_2e yr^{-1} in 2019 to 1.9 (32% reduction) and 0.7 Gt CO_2e yr^{-1} (73% reduction) in NDC and NDC+LTT respectively. The falling steel GHG intensity of production results in a lower contribution to industrial emissions. Aluminium emissions are much lower than steel and cement – but decrease from 0.21 Gt CO_2e yr^{-1} in 2019 to 0.08 and 0.05 Gt CO_2e yr^{-1} in NDC and NDC+LTT respectively. This is driven by strong reductions in GHG intensity of production, resulting from a switch to decarbonised refining options and inert smelting anodes, which today emit process CO_2 emissions as they are in operation.

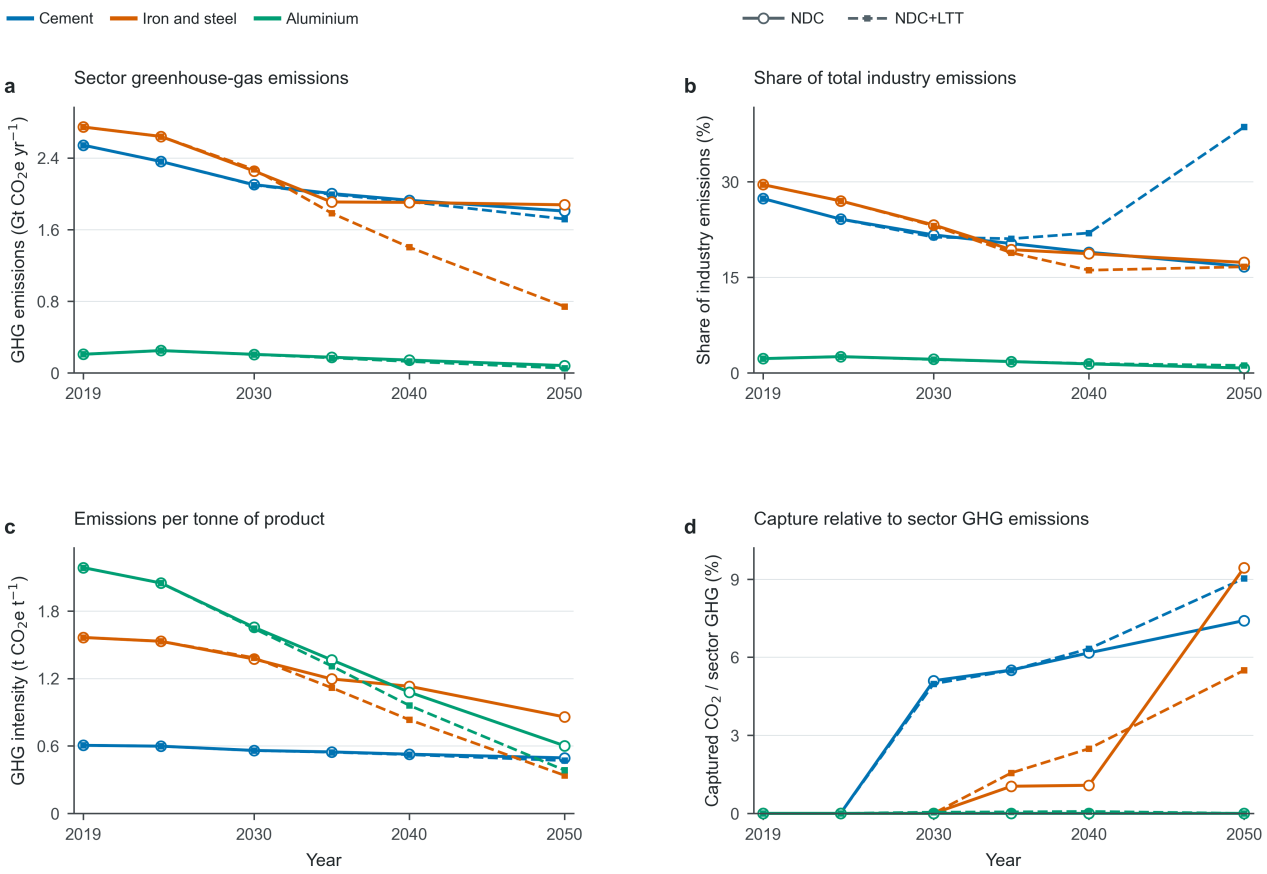

Figure 2.5. GHG emission metrics for basic material sectors under noCE cases in OMNIA-ENGAGE, 2019-50
a) Sector greenhouse gases; b) Share of industrial GHG emissions from basic material sectors; c) GHG intensity of sectors, based on ratio of emissions to production; d) CO_2 emissions captured via CCS technologies as a share of sector emissions.

2.3.2 Implementation of CE policies

The two key CE strategies explored in this study include: i) closing, to increase recycling of material stocks to enable a higher share of secondary production, and ii) narrowing, to improve material efficiency by lowering the input of materials into manufacturing and construction. As detailed in Table 2.1, these types of strategies are considered together in CE policy packages of different ambition – medium and high. In this section, the results of their implementation are assessed based on their implementation either in the EU only, or in the EU alongside a broader coalition of countries.

2.3.2.1 Reduced requirements for total and primary basic material production under CE policies

We first assess the impact of CE policy implementation on production. While CE policies lead to reductions in total production, increases in secondary shares (for metals) and reductions in clinker input (for cement), their contribution at the global level is much greater when applied in the EU and across international partners (M-EU+, H-EU+) (Figure 2.6).

For cement, global production increases by just over 1% when policies are introduced at the EU level. While the EU see reductions in production (Figure 2.7), regions outside of the EU policy implementation area see increases. This reflects complex dynamics; improvements in the efficiency of cement use lower the effective cost of producing construction services in the EU, stimulating construction output. This expansion partially offsets the potential reduction in cement use and increases demand for labour, capital and other materials. As the additional input demand from the construction sector exceeds the inputs released by the contraction of the cement sector, labour and capital prices rise across the EU. The resulting increase in production costs raises both domestic and export cement prices, further constraining EU cement production and exports. In response, regions outside the EU expand production to fill the resulting gap in the global market. This is an important type of insight from linking to a CGE framework.

A more global implementation reduces production by 5.6% (M-EU+) to 12.8% (H-EU+), depending on the policy package ambition. Clinker production falls more rapidly than cement production, resulting in lower clinker-to-cement ratios. For example, under H-EU+ ambition, clinker reduces by 22.3% under NDC, compared with the 12.8% reduction in cement. The resulting global clinker-to-cement ratio is approximately 0.63, compared to 0.71 in the equivalent noCE case. There is limited difference in the impact of CE policies in the NDC or NDC+LTT cases, as similar relative changes are implemented in both cases.

For both steel and aluminium, EU implementation does not have a significant impact at the global level, with around a 3% reduction in steel production, and either a small increase (medium ambition) or decrease (high ambition) for aluminium. Inevitably the reductions at the global level are going to be smaller due to the EU being a relatively small producer; however, the reductions are also limited due to rebound effects within the EU economy and adjustments in international markets, as discussed above. Decreases relative to the noCE case are much larger when implemented in concert with a broader set of countries. The secondary shares are also much higher in the EU+ implementation cases; for steel, the share rises from 36% (noCE) to 54% and 63% under medium and high ambition cases respectively. A similar pattern is observed for aluminium. As with cement, there is limited difference between NDC or NDC+LTT ambition levels for metals.

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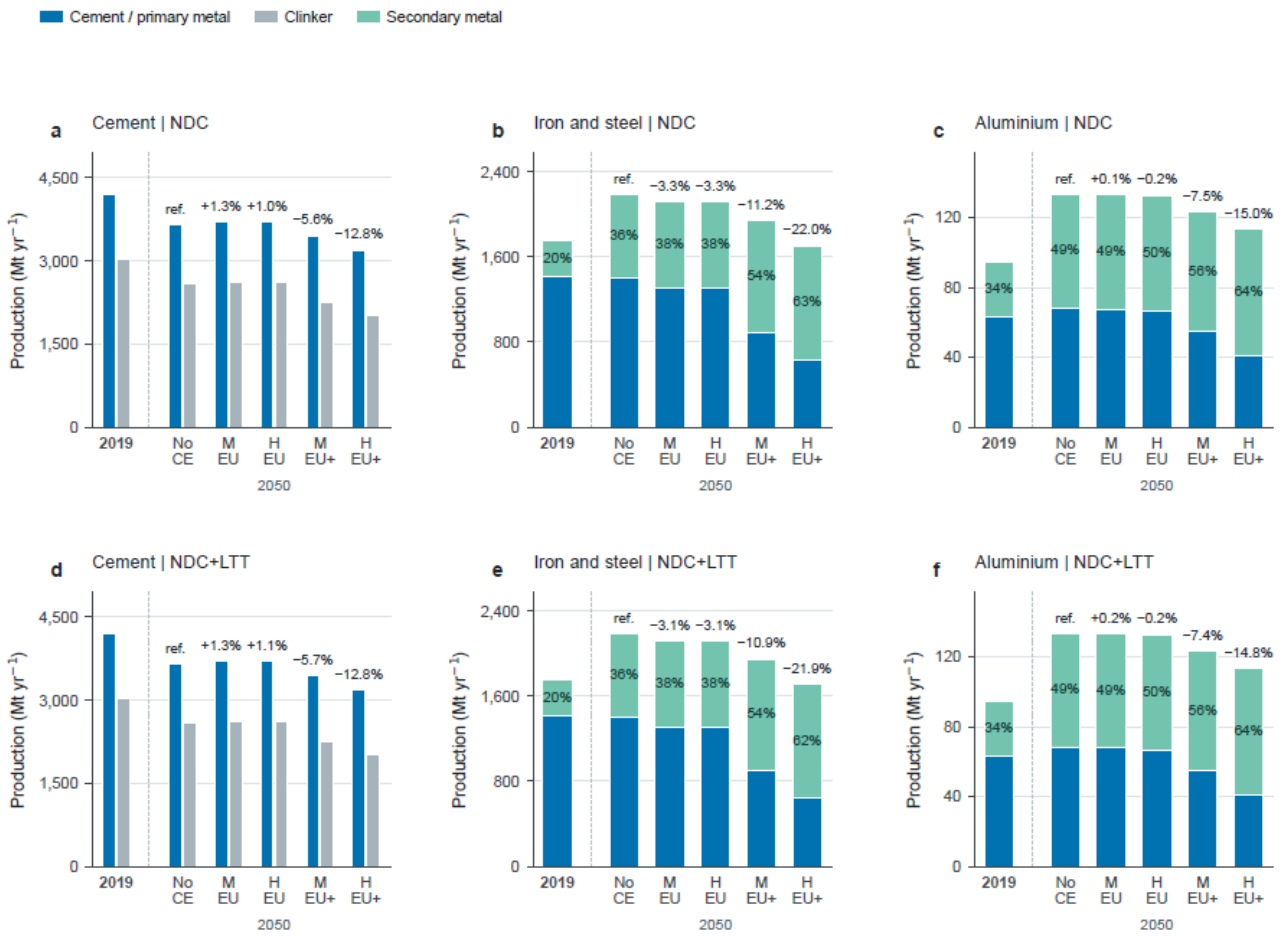

Figure 2.6. Global basic material production levels in 2050 across CE policy cases in OMNIA-ENGAGE, split by primary & secondary (metal) and cement & clinker

The top panel presents results for NDC scenarios, and bottom panel for NDC+LTT scenarios. M-EU and H-EU refer to scenarios where medium (M) and high (H) are implemented in the EU only; M-EU+ and H-EU+ are scenarios where CE policies have been introduced across a broader set of countries, in addition to the EU. Figures a & d show the change in production of cement and clinker in 2019, and across scenarios in 2050. The values above the bars show change relative to the noCE case for cement production. The other panel plots for metal b-c, e-f show the change across scenarios, but also the split between primary and secondary metals production. The values above the bars show change relative to the noCE case, while the values in the green bars are the shares of secondary production.

Figure 2.7 provides more clarity on the change in production in 2050 under the CE policy cases, for those countries in the policy implementation region and those outside. EU implemented policies in cement lead to reductions in EU production of 11% and 16% under medium (M-EU) and high ambition (H-EU), in both NDC and NDC+LTT cases (Figure 2.7a,d), which are also seen in the results from GCAM-Europe (Figure 2.8). These reductions are similar to those observed when implemented by both EU and partners e.g. in EU+ cases. In those areas outside of areas of implementation, the changes are small – notably because the number of countries and, therefore, the level of trade are much smaller, meaning policy stimulus has limited impact on other non-policy implementing countries.

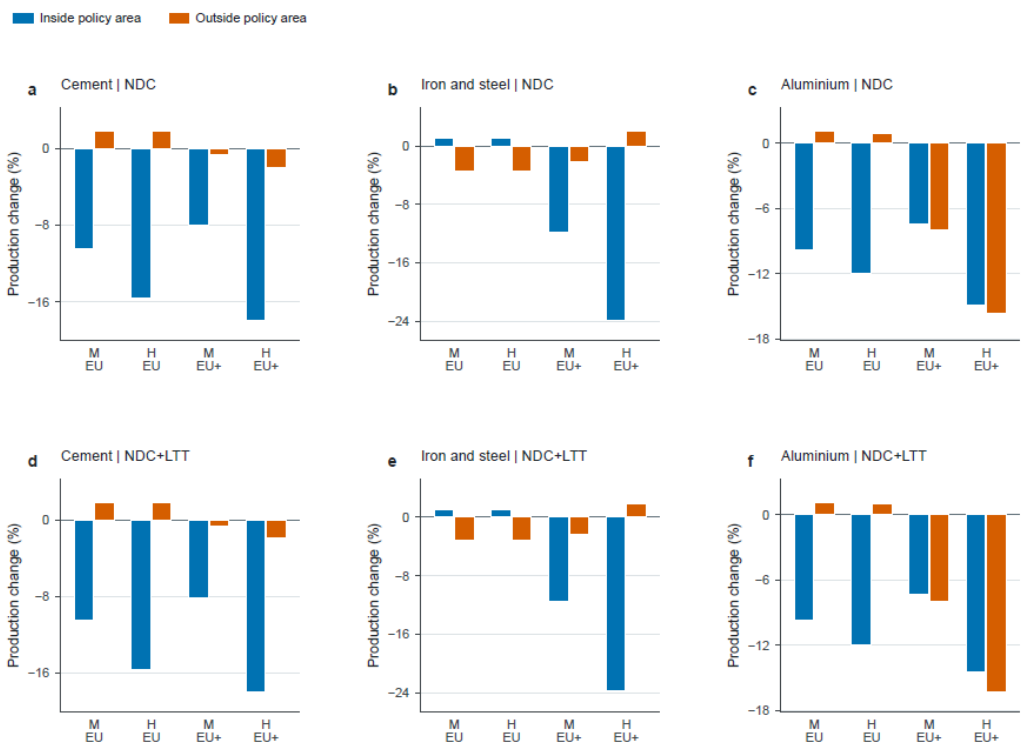

Figure 2.7. Change in basic material production levels in 2050 across CE policy cases in OMNIA-ENGAGE, relative to the noCE cases, inside and outside of designated policy implementation areas

Reductions are based on differences in production levels in the regions that are inside or outside, not relative to global levels (as per earlier charts). Upper panel shows NDC scenarios, and lower panel NDC+LTT scenarios.

The iron and steel sector shows a similar pattern to that observed for cement, except that EU only implemented cases do not lead to reductions within the EU bloc. As noted earlier, this is due to efficiency savings driving cost reductions in steel-using sectors, lowering prices and enabling more production and exports; in essence, a rebound effect. This contrasts with the reductions in GCAM-Europe of 5-7.5%, notably because the economic rebound effects are not modelled (Figure 2.8). For EU only adoption, aluminium sees a similar pattern to cement, with reductions in the bloc of 10 and 12% under medium and high ambition, and minor increases in production outside the EU area. Note that GCAM-Europe did not represent material efficiency reductions for the aluminium sector. For cases with implementation in the EU and across wider partners, similar levels of reductions are observed both in and outside of the implementation areas.

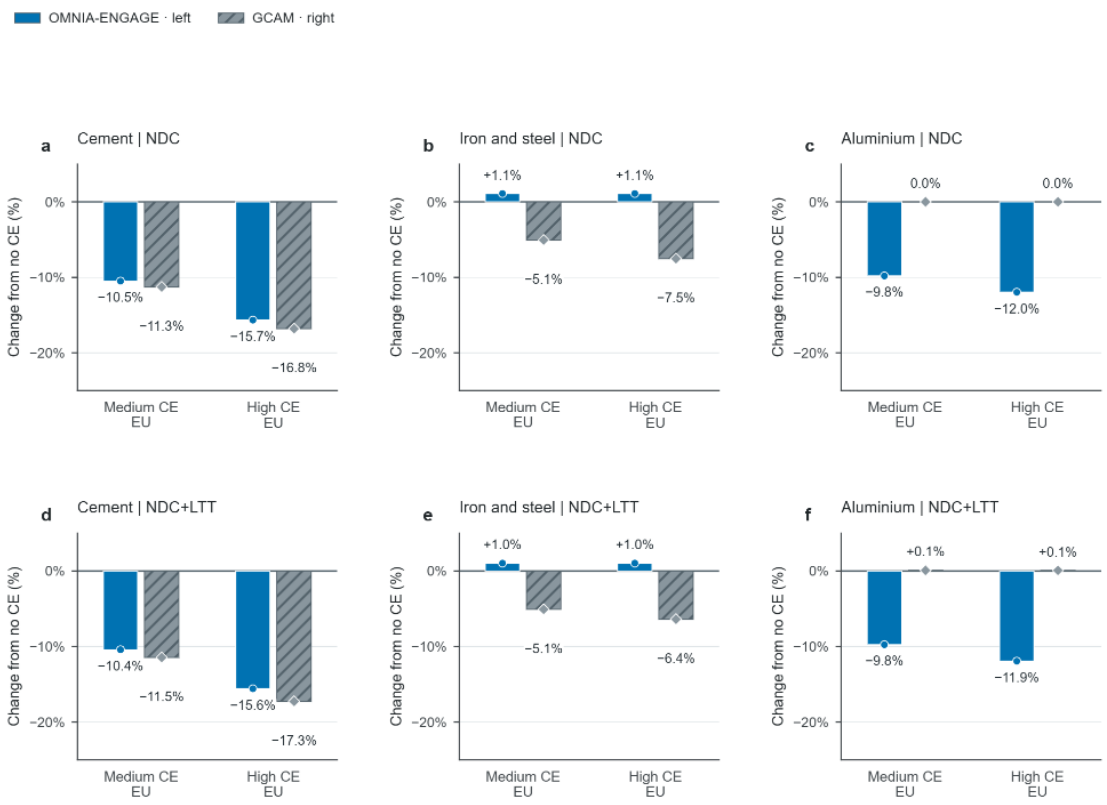

Figure 2.8. Change in basic material production levels in 2050 in the EU across CE policy cases in OMNIA-ENGAGE and GCAM-Europe, relative to the noCE cases
Note that GCAM-Europe did not represent material efficiency reductions for the aluminium sector.

2.3.2.2 Sectoral energy requirements fall as production levels reduce and secondary production shares increase

All sectors see lower energy demand as a result of CE policies, again with higher global reductions from a wider geographic implementation. The H-EU+ case reduces cement, steel and aluminium energy demand by 21%, 47-51% and 38% respectively, under the two climate ambition levels. In the steel sector, NDC+LTT highlights how the most ambitious CE policies help remove the majority of fossil fuel use from the global sector when implemented more widely (H-EU+ in Figure 2.9e), with electricity dominating, complemented by a small amount of hydrogen. Technology wise, the sector is underpinned by molten oxide electrolysis, hydrogen direct reduction and secondary production via electric arc furnaces. The lower climate ambition of NDC sees some coal remaining in the mix in 2050 in the equivalent scenario (H-EU+ in Figure 2.9b).

Results for the steel sector in OMNIA-ENGAGE can be compared to those provided by OPEN-PROM (Figure 2.10). In the EU+ case under NDC ambition, energy reduction levels in 2050 are double those observed in OPEN-PROM (relative to noCE case). This likely reflects a combination of more ambitious low carbon primary and secondary production diffusion with greater uptake of material efficiency in OMNIA-ENGAGE. There are limited reductions in OPEN-PROM from CE policies under NDC-LTT (compared to the noCE case), indicating limited further potential in this model to decarbonise in this climate policy future. This is in part reflective of a need for further representation of distinctive primary and secondary production pathways within OPEN-PROM. This comparison also highlights the need for additional research to explore the economics and resulting uptake of different steel technologies.

For aluminium, while overall fuel demand decreases, the mix of energy types remains similar, given the dominance

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of electricity and the continued use of small amounts of gas and hydrogen for refining and thermal energy in secondary production (Figure 2.9). Cement follows a similar trend to aluminium, with fuel shares in final energy demand remaining broadly alike while cumulative demand reduces. That said, it is important to note that within the solids category there is a switch from coal to biomass fuelling.

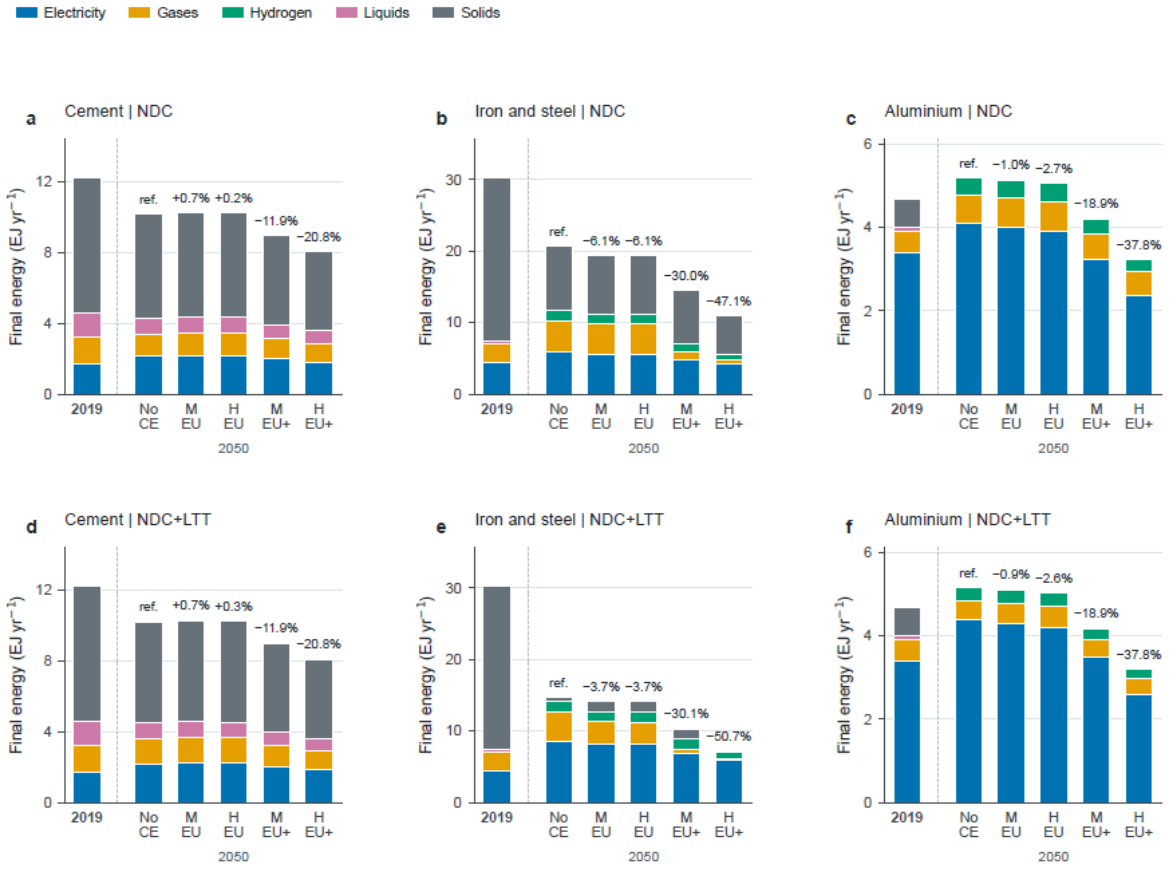

Figure 2.9. Final energy use by global sector in 2050 across CE policy cases in OMNIA-ENGAGE
Top panel shows energy use by type for the NDC scenarios, and bottom panel shows NDC+LTT scenarios. Values on the top of bars are total energy reductions relative to the 2050 noCE case.

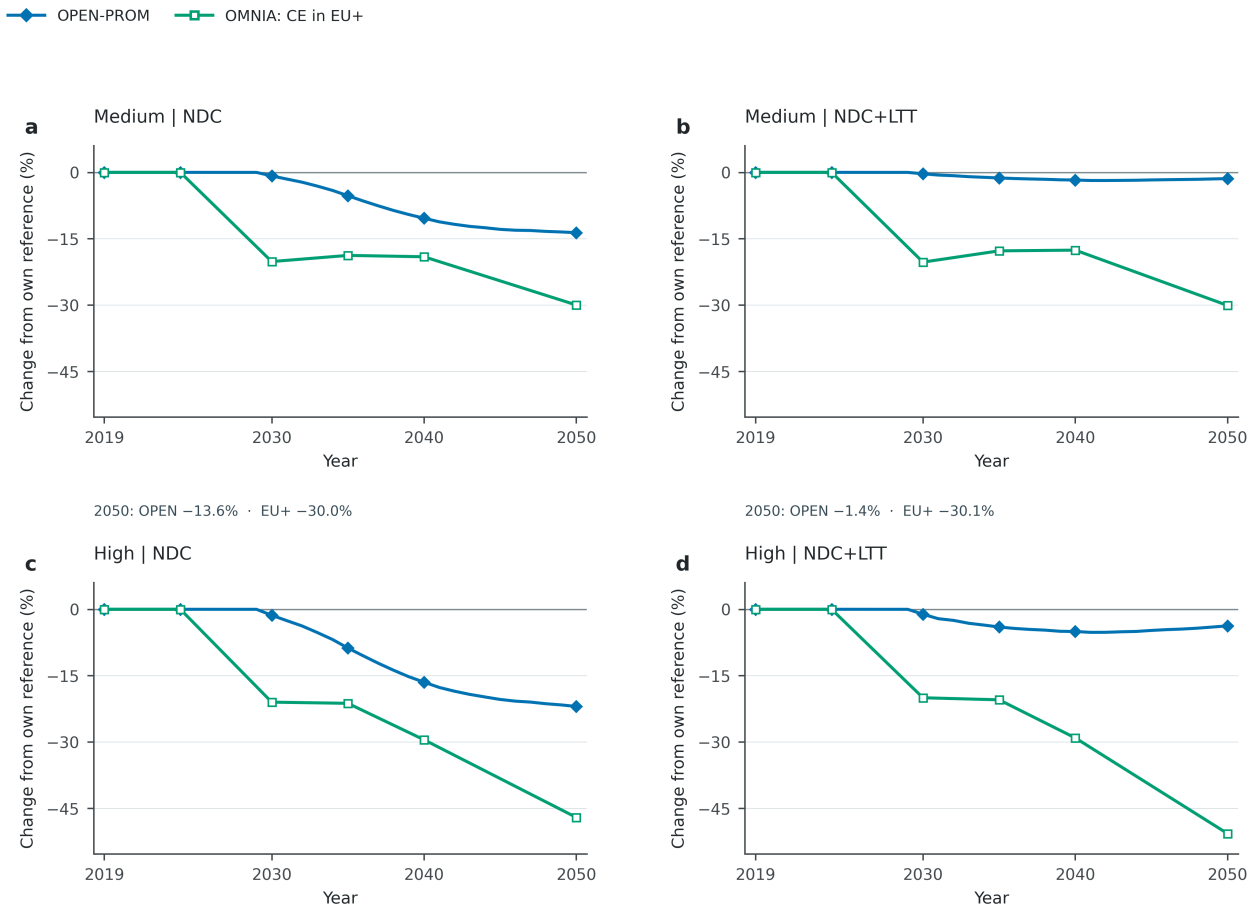

Figure 2.10. Change in final energy use for iron and steel sector under high and medium CE ambition cases (relative to noCE) based on EU+ implementation in OMNIA-ENGAGE and OPEN-PROM

Changes in energy demand can be further assessed for the EU and EU plus partners ('inside policy area'), and for the regions outside where no policy implementation takes place ('outside policy area'). For cement, the reductions in Figure 2.11 follow the change in production (Figure 2.7). A similar pattern of reduction, albeit not as large, is observed in the results from GCAM-Europe (Figure 2.12). For iron and steel, the sizeable reductions in the EU region are a function of much more aggressive secondary production increases relative to the noCE case (as per differences between values in Table 2.1 and Table 2.2). The reductions are primarily for electricity, as the noCE case already has significant levels of uptake of electricity-based primary steel production by 2050. This is an assumption that will be revised in future analysis. The reductions observed for GCAM-Europe are lower than observed for ENGAGE-OMNIA, and reflect reductions in the use of fossil fuels (Figure 2.12). For EU+, reductions in the policy region are due to a drop in production levels and again increased secondary shares; for countries outside the policy area, the increase is a result of a lower secondary share versus the noCE case.

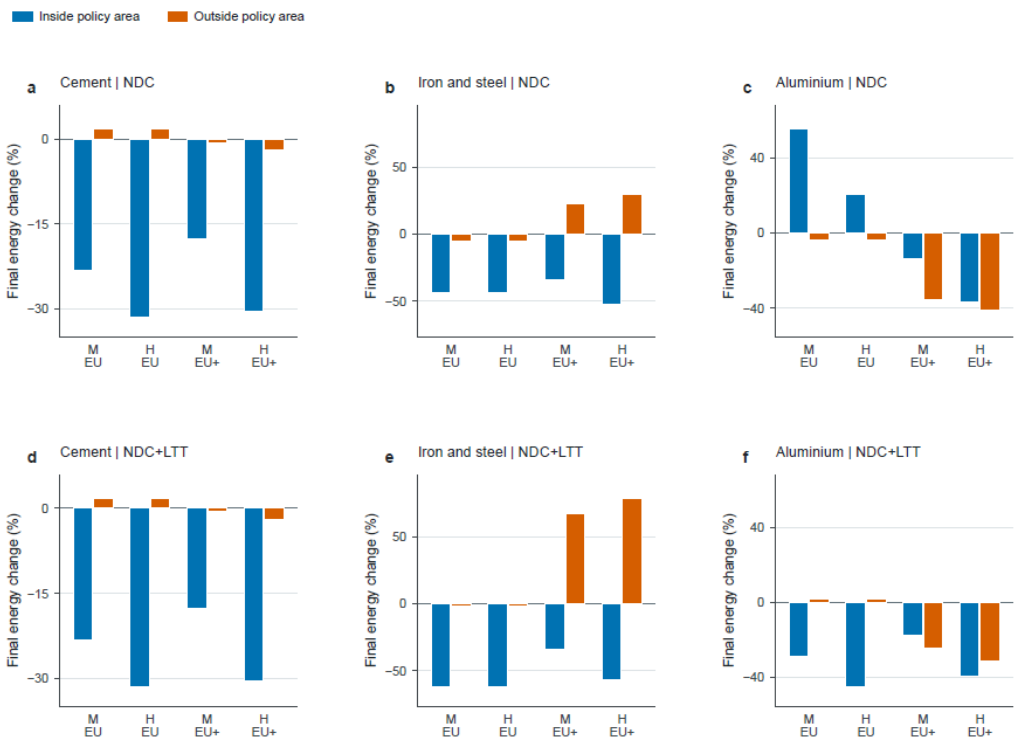

Figure 2.11. Change in final energy use in 2050 in CEP policy cases in OMNIA-ENGAGE, relative to the noCE cases, inside and outside of designated policy implementation areas

Reductions are based on differences in energy demand in the regions that are inside or outside, not relative to global levels (as per earlier charts). Upper panel shows NDC scenarios, and lower panel NDC+LTT scenarios.

In the case of aluminium, final energy demand reductions are observed for NDC+LTT under both regional groupings and for the NDC scenario under the EU+ grouping due to the combination of changing secondary shares and production (Figure 2.11). For the NDC scenario and EU grouping, final energy demand relative to the noCE baseline increases in the EU because the secondary share in these regions decreases, i.e. in the noCE scenario these regions have higher secondary shares because of the nature of how the baseline was setup. These effects are seen in the comparison with GCAM-Europe, in Figure 2.12. Under the NDC-LTT case, the GCAM-Europe results are much lower due to the assumption of no material efficiency gains.

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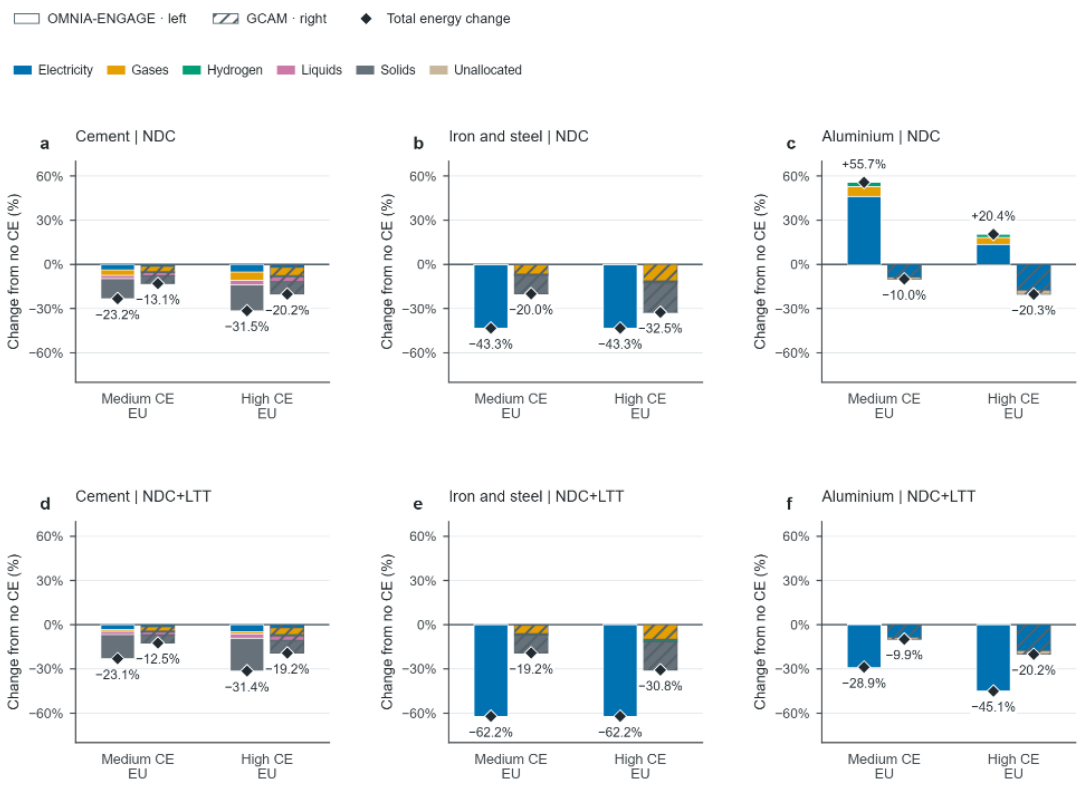

Figure 2.12. Change in basic material sector final energy use in 2050 in the EU across CE policy cases in OMNIA-ENGAGE and GCAM-Europe, relative to the noCE cases for each respective model.

2.3.2.3 GHG implications of CE policy packages and regional implementation

Figure 2.10 highlights the emissions reduction implications of the introduction of CE measures, which depends strongly on adoption scope and on the emissions boundary considered. Without CE policies, emissions from the three sectors of focus reach 3.8 and 2.5 Gt CO_2e yr^{-1} under NDC and NDC+LTT respectively in 2050, from a 2019 level of 5.5 Gt CO_2e yr^{-1}. The medium (M-EU+) and high level (H-EU+) ambition with policy action in non-EU partner countries lowers GHG emissions to 2.5 (-32%) and 1.6 Gt CO_2e yr^{-1} (-37%) respectively in 2050 (Figure 2.13a-b). This highlights the strong role that CE policies can play, in further reducing sectoral emissions – and the global impact of effective coordination on policy action.

We next consider the change in industrial emissions in 2050, relative to the noCE case, and the contribution from the three basic material sectors (Figure 2.13c-d). In the NDC case, the CE policy measures result in reductions for the sector as whole. For example, in the H-EU+ case, emissions from the three sectors fall by 1,220 Mt CO_2e yr^{-1}; a small increase from the rest of the sector leads to a net reduction of around 1,160 Mt CO_2e yr^{-1} for the industry as a whole. Under NDC+LTT, there is a stronger increase in other industry emissions, with CE policies in the three sectors providing some flexibility for other parts of industry not to take high-cost mitigation actions; hence their relative increase compared to the noCE case (Figure 2.13d).

In terms of individual sectors, it is the iron and steel sector that contributes the most to GHG reductions in OMNIA-ENGAGE, with OPEN-PROM also showing strong emission reduction potential from CE measures for the sector (Figure 2.14c-d). Despite relatively lower final energy reductions in OPEN-PROM (Figure 2.10), GHG reductions are more aligned, indicating that the energy reductions have a higher per unit emission reduction benefit. NDC reductions are closely aligned between the models, while NDC+LTT reductions are larger in OMNIA-ENGAGE.

EU GHG reductions from CE measures appear limited in the global context (as shown in left hand columns of

Figure 2.13c-f) but are important at the region level, as shown in Figure 2.14a,b. This shows reductions of 5.5-8.2% under NDC and 8.5-15.5% under NDC+LTT for OMNIA-ENGAGE. GCAM-Europe confirms a contribution to GHG reductions across the three sectors, although at slightly lower levels in most cases.

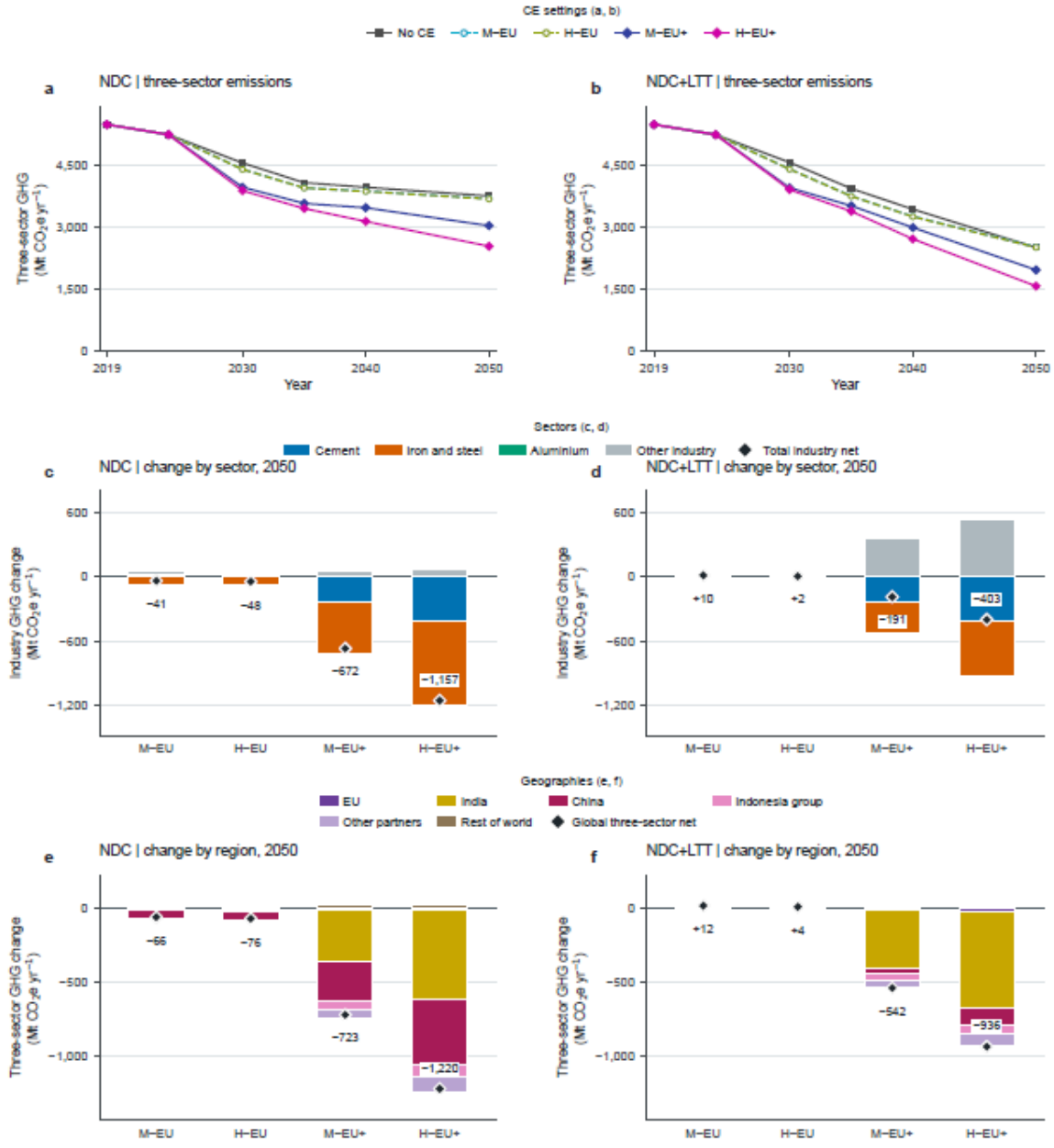

Figure 2.13. Global GHG emission reductions associated with basic material sectors under CE scenarios from OMNIA-ENGAGE

Top panel (a-b): basic material sector GHG emissions, 2019-50; Middle panel (c-d): change in GHG emissions by basic material sector in 2050 relative to noCE cases; Bottom panel (e-f): contribution to overall CE reductions in 2050 by EU and partner countries at the aggregate 3-sector level. These metrics do not include indirect GHG emissions associated with electricity generation.

Finally, we can also assess the contribution by country or region to the reductions observed across the three sectors. Under the NDC case, the largest reductions in the EU+ scenarios come from India and China by 2050, as the largest basic material producers. In the EU scenarios, GHG emissions in the EU increase slightly, as the region of CE policy implementation sees higher iron and steel production, while China sees a small reduction in emissions because regions with no CE policies see a decrease in steel production. This is a result of economic rebound within ENGAGE. In the NDC+LTT case, reduction in the EU+ scenarios is dominated by India, where the potential for emission reductions is the highest given the combination of production levels that are comparable with China in 2050 but with higher carbon prices. This latter point occurs because India's emissions target trajectory in 2050 in the NDC+LTT case is approximately 33% that of China's but with an economy 60% the size.

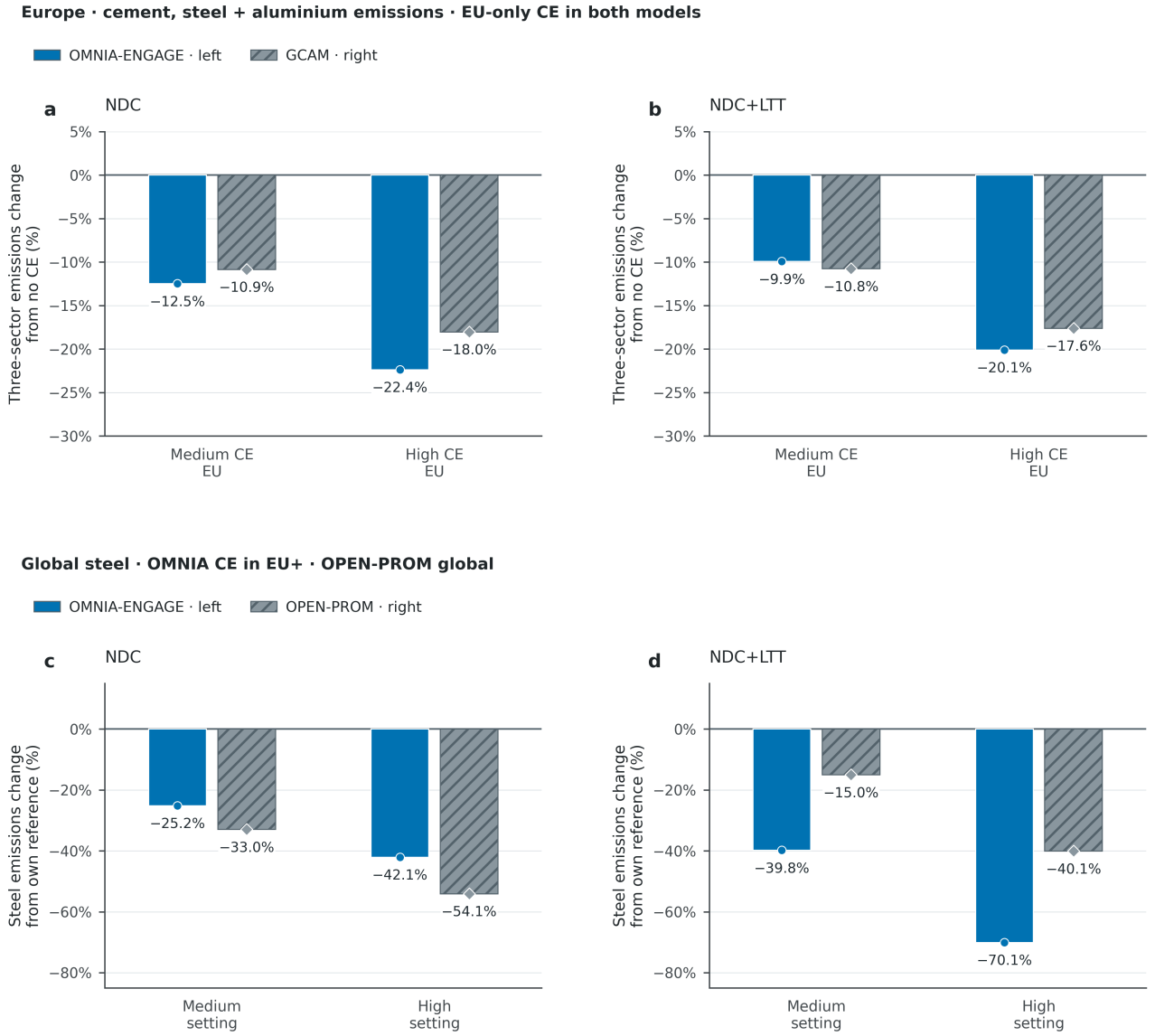

Figure 2.14. Comparison of modelled GHG emission reductions associated with basic material sectors under CE scenarios, relative to noCE cases

Upper panel: EU regional GHG reductions for all three basic material sectors under GCAM-Europe and OMNIA-ENGAGE modelled scenarios. Lower panel: Global reductions for iron and steel sector under OPEN-PROM and OMNIA-ENGAGE modelled scenarios.

2.3.2.4 System cost implications of CE policy implementation

The impacts of CE measures are first estimated in ENGAGE (representing the full economy) and then passed to OMNIA (representing the energy system). We first assess the cost implications of these CE measures on the energy system. With higher shares of more cost-effective secondary production, and a reduction in production requirements due to material efficiency measures, inevitably the costs for the system reduce (Figure 2.15). This is particularly the case when CE policies are implemented in both EU and partner countries. Global sector costs in 2050 relative to the noCE cases are 18%, 46% and 45% lower for cement, steel and aluminium respectively in the H-EU+ case, under NDC climate ambition, with a very similar pattern observed for NDC+LTT. For medium ambition CE policies (M-EU+) in the NDC, reductions are lower at 10%, 33% and 23% respectively (again with similar reductions under NDC+LTT). Cost reductions for cement are lower than those observed for metals sectors because the sector partially switches from coal fuelled to biomass fuelled production with both routes having similar cost implications.

EU-only packages yield more limited reductions (at the global level) and even some cost increases. In 2050, cement costs rise by 0.5–0.8% under NDC and 0.7–1.0% under NDC+LTT. In both cases this is because production increases in regions without CE policies in our ENGAGE modelling. Steel costs decline by around 6% and 10%, respectively across climate cases, while aluminium reductions remain below 3%. This reflects the dynamics around production levels associated with CE policies, as discussed earlier.

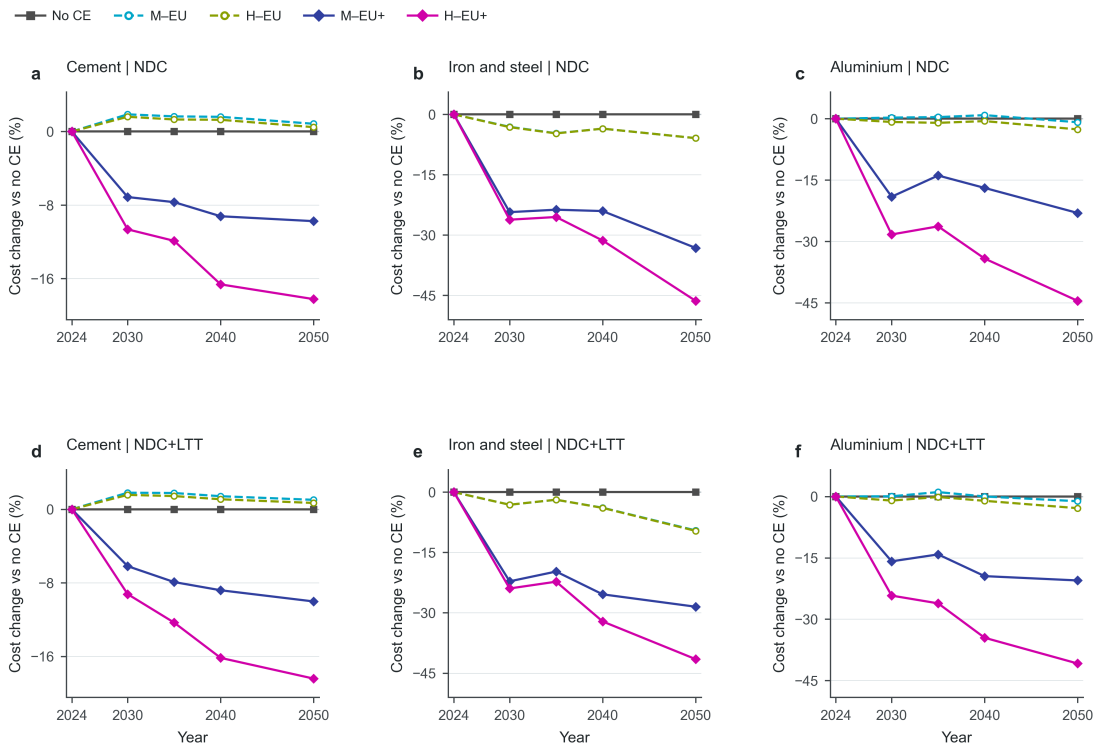

Figure 2.15. Percentage change in global annualised costs for basic material sectors under CE scenarios in OMNIA-ENGAGE, relative to noCE case, 2024-2050

Upper panel shows sector plots for three sectors of focus under NDC climate ambition, while lower panel shows the same information for NDC+LTT.

2.4 Discussion and conclusions

There are a number of key findings that emerge from this modelling analysis. Firstly, CE policies (and associated measures) lead to a wider portfolio of mitigation measures that can enable additional GHG reductions from basic material sectors, notably cement and steel. This is largely through increased secondary production due to higher recycling rates in the economy, and reduced material input into industrial activities i.e. material efficiency. This is critical for these sectors that are arguably more challenging to decarbonise due to the long asset lifetime of existing stock, and the energy intensity of primary production. Under a high ambition CE package implemented by EU and partners (H-EU+), under stronger climate policy (NDC+LTT), CE measures reduce GHG emissions by 1.3 (-32%) and 0.9 Gt CO_2e yr^{-1} (-37%) by 2050 not including reductions in indirect emissions associated with electricity generation. This increased contribution provides more headroom for GHG emissions from other industrial sectors or indeed other sectors in the wider energy system, notably in the case of NDC+LTT. This suggests that increased promotion of CE measures in other subsectors could reduce industrial emissions further, boosting the overall contribution of the industry sector to the delivery of climate targets. Findings from OPEN-PROM for the steel sector largely corroborate this, although OMNIA-ENGAGE show more ambition and thus greater emissions reductions in an NDC+LTT future.

Secondly, the analysis highlights that wider co-operation on industrial CE strategy beyond the EU is key for realising larger global benefits. Implementation of policies in conjunction with international partners results in much larger reductions in global emissions. This should not diminish the significance of the sizeable relative reductions within the EU, which are confirmed by GCAM-Europe, although OMNIA-ENGAGE shows a greater emissions impact. The smaller absolute reductions reflect the fact that large production bases are located elsewhere. Our analysis suggests that key economies of focus include China and India, given their position as major producers of basic materials, both now and in the long term. Furthermore, co-operation matters for another reason; there is evidence from the CGE modelling that the EU acting alone may not realise the gains due to rebound effects. CE policies can increase relative economic competitiveness, resulting in higher levels of production and offsetting potential reductions. A more coordinated approach internationally could minimise such rebound effects, if production across more countries is also subject to similar CE policies.

Thirdly, CE measures can also lead to cost reductions across the industrial sectors of focus, due to an increase in the share of lower-cost secondary production and lower levels of production overall. This is observed across all sectors, although is highest for aluminium and iron and steel. This is important for reducing the costs of mitigation and, in so doing, helping to support the wider feasibility of delivering the energy transition in general. This is evident from assessing the carbon prices that are output by OMNIA-ENGAGE. In India, carbon prices in 2050 are halved when CE policies are introduced, from approximately $900 to $400 per tonne CO_2e in the NDC case, and from $1100 to $550 per tonne CO_2e in the NDC+LTT case. While these are proxy carbon prices, they do show a strong reduction in mitigation costs for the large producing countries. European carbon price differentials are much smaller, due to the relative size of emissions from these sectors relative to the wider energy system. While differentials in carbon price reductions due to CE policies differ, the trend towards lower mitigation costs is observed in all regions.

Finally, it is important to highlight the wider benefits of CE policies, not only in respect of supporting climate mitigation objectives – but in promoting resource efficiency and waste reduction in basic materials. This not only helps reduce the costs of mitigation but could benefit the wider economy by reducing material inputs into other industrial sectors, and making the most of existing stocks of materials that can be recycled and re-used. In this respect, it is also true that strong climate policies can mutually reinforce increased CE ambition, notably through carbon prices that provide the incentives towards increased secondary production, lower clinker use and broader material efficiency.

In summary, this analysis points towards an important contribution of CE policy packages in delivering regional and global climate goals – and supports the body of evidence that points in this direction, as summarised earlier in this report. It also highlights the importance of broader cooperation between EU and international partners on CE strategies to maximise the benefits for basic material sectors, some of which are highly traded and exposed to international competition. Furthermore, methodologically it demonstrates the benefits of linking macroeconomic and integrated assessment models for the exploration of circular economy futures and model inter-comparison for additional validation.

There are a number of areas for further refinement of this analysis going forward. These include –

- *Linking (of OMNIA-ENGAGE models)*. The GDP implications of CE policy implementation in ENGAGE were not directly coupled with OMNIA. This is relevant for various sectors beyond the three of focus here. Addressing this would ensure a stronger linkage between models. A further improvement of the linkage would be more explicit consideration of the scrap material flows from ENGAGE, including their trade between regions.
- *Further review of technology uptake*. A stronger focus on the deployment of key technologies requires further refinement. This includes the competition between molten oxide electrolysis and hydrogen DRI for steel making, and the role of bioenergy in the cement sector versus CCS deployment. These technologies have strong impacts on the supply of energy to the sector – and the resulting energy and carbon intensity. More scrutiny of their deployment – and non-cost factors that might speed up or slow their deployment – would be useful to consider further.
- *Assessing a broader range of CE strategies and across more sectors*. Given the promising role that CE measures can play in industrial decarbonisation, further assessment of a broader range (across narrowing, slowing, and closing strategies) would be insightful – for clarity on the relative strength of different measures. Furthermore, consideration across other sectors e.g. chemicals, for a more holistic view of the role CE policies can play in industrial decarbonisation, would also be a promising avenue to explore.

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3 The distributional impacts of net-zero targets in Europe

3.1 Introduction

Integrated Assessment Models (IAMs) are the main workhorse for the development of scenarios of long-term climate change mitigation, with carbon pricing being one of the core policy instruments applied. The literature on IAMs of the last decades has increasingly considered and integrated socio-economic conditions in the economy, which in turn determine the economic growth path and its structure, even occasionally getting closer to 'de-growth' approaches (e.g., Mastini et al., 2021; Parrique, 2019). Formally, IAMs integrate representations of the energy system, land use, the macroeconomy and the climate system into a single quantitative framework, and they have guided climate-policy analysis from the early cost–benefit models (Nordhaus, 1992) through to the scenario exercises underlying successive IPCC assessment reports. Two broad families of interest to our work in this section dominate the field: intertemporal optimisation models, which derive cost-efficient mitigation pathways, and recursive-dynamic computable general-equilibrium and system-dynamics simulation models, which trace out adjustment processes, as well as rigidities and feedbacks over time.

Because long-run mitigation scenarios are highly sensitive to the assumed socio-economic drivers – such as population, GDP, technological options and the distribution of income – the modelling community has moved from arbitrary reference scenarios to the Shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2014; Riahi et al., 2017). The SSPs define five narratives about future societal development – SSP1 'sustainability', SSP2 'middle of the road', SSP3 'regional rivalry', SSP4 'inequality' and SSP5 'fossil-fuelled development' – which are quantified with IAMs and combined with the Representative Concentration Pathways (RCPs) in the scenario matrix that underpinned IPCC assessments (before the adopted classifications in AR6). Within this framework, income distribution enters primarily as an exogenous scenario assumption – most visibly through Gini-based inequality projections ((Rao et al., 2019), see Section 3) – rather than as an outcome generated inside the models.

In general, the model-based literature on how climate change mitigation policy affects the distribution of income, covers three related strands: (i) micro-empirical incidence studies of carbon and energy taxes in high-income economies, (ii) comparative and meta-analytic evidence from low- and middle-income countries, and (iii) integrated assessment modelling that embeds household heterogeneity and links mitigation pathways to the SSPs. The unifying question across all three strands is not whether mitigation has distributional consequences, but under which conditions (income concept, country income level, general-equilibrium channels, and revenue use) those consequences are progressive, regressive, or reversible by policy design.

One precondition for analysing the interconnection between mitigation policy and income distribution is the integration of income and consumption structures of different household types in models; an approach that was presented in the DIAMOND project within Deliverable D4.3, where a household dataset has been established and made available to several IAMs (GEMINI-E3 EU, NEMESIS-World and GCAM-Europe) used in the project.

The purpose of this section of the report is to describe how income distribution, varying across socio-economic scenarios, exerts feedback mechanisms on CO_2 mitigation policy. Income distribution and emissions have been widely analysed in the carbon footprint-literature in a static footprint framework, i.e., to address aspects related to which household types contribute which amount to the total carbon footprint of an economy. For analysing and evaluating climate policy scenarios, a dynamic framework is needed that enables analysis of how income distribution changes with different mitigation instruments (carbon pricing vs. regulation).

This question of the distribution impacts of mitigation policy has not been dealt with in depth in the literature. In general, the empirical evidence on this question is mixed, as shown in Section 3.2. Beyond the incidence of carbon

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pricing itself, the section also reviews recent evidence on the reverse feedback – from redistribution to emissions – including integrated-assessment simulations of a universal basic income financed by wealth and carbon taxation (Arto et al., 2027), which show that distributional policy can itself affect mitigation outcomes through aggregate demand. For the analysis within the DIAMOND project, income distribution aspects are linked to the SSP-framework that is applied in IAMs and to concrete policy instruments. The empirical application of the household dataset of DIAMOND to the scenario work with the models GCAM-Europe and NEMESIS (Section 3.3 and 3.4 respectively) gives insight into how income distribution affects modelling outcomes as well as how the policy impact depends on household characteristics. Finally, we derive some recommendations for policy makers and system modelers, in Section 3.5 "Conclusions".

3.2 Empirical evidence: Is carbon pricing regressive?

3.2.1 Aggregate evidence across countries

The starting point for this literature is the observation that, in high-income economies, energy expenditure as a share of income tends to fall as income rises — so a uniform carbon price, absent compensation, tends to be regressive. Poterba's (1991) analysis of US gasoline taxation established this empirical pattern and became the reference point in the subsequent debate. Rausch et al. (2011) showed that the apparent regressivity of a US carbon tax is substantially reduced — though not eliminated — when incidence is measured against *lifetime* rather than *annual* income, since annual income captures transitory fluctuations (e.g., retirees or the temporarily unemployed) that overstate the burden on the low income-households.

Sterner (2012) edited volume *Fuel Taxes and the Poor* assembled comparative country evidence broadly confirming the finding of regressive impacts in the OECD-context, while also showing meaningful cross-country variation, depending on car ownership and transport-fuel demand patterns. Pizer and Sexton (2019) provide a systematic review of this literature and conclude that regressivity is a robust but not universal finding. The incidence depends on which energy commodities are taxed, the physical/social/climatic characteristics of the jurisdiction, and — above all — how tax revenue is used. This last point is demonstrated directly by Cronin et al. (2019), who use US Treasury microdata on 322,000 households to show that a carbon tax's *vertical* incidence (rich vs. poor) becomes progressive once the statutory indexing of transfers is accounted for, and even more so once revenue is rebated — though they also identify large horizontal redistribution (unequal burdens among households at the same income level, due to heterogeneous energy intensity of consumption), which may be seen as a desired result of the policy.

Douenne (2020), studying the French carbon tax using microsimulation, reaches a similar conclusion: the policy is regressive on a pure price basis, but can be made progressive via lump-sum per-household recycling, though this still leaves large horizontal effects that disproportionately harm rural and peri-urban low-income households. In this context, it is worth to differentiate between the carbon tax burden of poor or low income-households vs. the burden of vulnerable households. Within this latter group of vulnerable households, it is also worth differentiating between households with adjustment potential (e.g. urban households with high quality-infrastructure) and 'trapped' households. This categorisation might also be correlated with income, which gives a complicated picture.

A second strand shows that the regressivity finding from high-income countries is not a general result. Dorband et al. (2019) conduct a global comparative analysis across low- and middle-income countries and find that carbon pricing tends to be progressive or distributionally neutral in this context: the poorest households often lack access to modern energy carriers (electricity, vehicle fuel) altogether, producing an inverse-U-shaped relationship between energy-expenditure share and income, rather than the monotonically declining share observed in rich countries. A carbon price of USD 30/tCO_2 was found to reduce income by up to 2.5% for the poorest households,

with the effect driven mainly by indirect rather than direct energy costs.

Ohlendorf et al. (2021) formalize this into a meta-analysis of 53 empirical studies (183 estimated effects across 39 countries), using an ordered-probit meta-regression. They confirm systematically higher odds of a progressive outcome in lower-income-country studies and in studies of transport-fuel (rather than heating/electricity) pricing, as well as in study designs that incorporate indirect effects, demand-side behavioural adjustment, or lifetime-income proxies. The conclusion is that much of the apparent disagreement about the distributional impact in the earlier literature reflects methodological choices rather than genuine cross-study disagreement.

3.2.2 Evidence from a macroeconomic perspective

Another strand of the literature emphasizes that partial-equilibrium household-expenditure incidence studies can materially understate — or mischaracterize — the true distributional burden, because they omit general-equilibrium channels operating through employment, wages and capital income. Känzig (2023) exploits high-frequency price surprises around EU ETS auctions as a source of exogenous variation and finds that a tightening of carbon pricing acts, in aggregate, like an adverse energy-price shock: poorer households cut consumption substantially more than richer households, both because of a higher direct energy-expenditure share and because they experience a larger fall in income. Roughly two-thirds of the aggregate consumption response is estimated to operate through indirect general-equilibrium channels (income and employment effects) rather than direct energy costs — implying that the true incidence of carbon pricing is more skewed toward low-income households, and more macroeconomically consequential, than static expenditure-based studies suggest. Lower-income countries were also found to experience larger (if not statistically distinguishable) output losses from the same shock.

Budolfson et al. (2021), using the Nested Inequalities Climate-Economy (NICE) integrated assessment model, show that this general-equilibrium incidence problem is a matter of policy design, not an inherent feature of carbon pricing: if carbon-tax revenue is returned to citizens as an equal per-capita dividend, an ambitious global mitigation pathway (consistent with the 2°C-target) can simultaneously reduce emissions, reduce inequality, and reduce poverty, with benefits materializing quickly. Critically, the same model shows that without progressive revenue use, the poorest households are made worse off in the short-to-medium run even as long-run climate benefits accrue. That reinforces the message from the meta-analysis literature above that recycling design is typically the dominant determinant of net incidence, often more so than the carbon price path itself. This result is in line with the large body of the literature about the 'double dividend hypothesis' in macroeconomic terms, which also assigns the major role of the impact to revenue recycling of carbon taxes (Fricke et al., 2025).

A complementary piece of evidence comes from the ecological-macroeconomic branch of IAMs, in which both income distribution and emissions are endogenous within a demand-driven simulation framework. The fourth strand is the one most directly relevant to integrated-assessment and household-heterogeneity modelling: how income-distribution assumptions are embedded in, and interact with, the SSP scenario framework used throughout climate-economic modelling. Integrating income distribution into economy–energy–climate modelling is therefore not entirely new, but it remains under-researched. A first generation of household-disaggregated applied general-equilibrium models already analysed the incidence of energy and carbon taxation in the 1990s, and consumption-based carbon-footprint accounting has long documented a steep gradient of emissions with income, within and across countries (e.g., (Sommer & Kratena, 2017; Wiedenhofer et al., 2017)). The cross-country evidence on how inequality relates to emission levels is, however, mixed and theoretically ambiguous – the relationship appears to be curvilinear, with its sign depending on the level of development (Grunewald et al., 2017) – and prospective thought experiments on global income redistribution point to potential trade-offs between equity and climate objectives (Millward-Hopkins & Oswald, 2021; Oswald et al., 2021), even

though other work suggests that lower global inequality could itself improve climate outcomes (Rao & Min, 2018). What is comparatively new is the embedding of these mechanisms in the IAM scenario framework used for mitigation policy: most global IAMs still represent a single representative household per region, treat inequality as an exogenous SSP input, and report macro-aggregates only. The slow uptake reflects the scarcity of harmonised household microdata at the global scale, the technical burden of coupling microsimulation or detailed demand systems to large models, and the persistence of the representative-agent paradigm in optimisation-based IAMs. Research has accelerated only recently, with projections of full national income distributions consistent with the SSPs, poverty microsimulations coupled to mitigation pathways, and the first multi-model assessments with inequality-aware IAMs (Emmerling et al., 2024).

(Rao et al., 2019)constructed the income-inequality (Gini) projections that underlie the SSPs: an econometric model driven by total factor productivity growth, educational attainment, and social public spending. The resulting Gini trajectories differ systematically by SSP narrative — SSP1 (sustainability) and SSP5 (fossil-fuelled development) trend toward lower inequality, while SSP3 (regional rivalry) and SSP4 (inequality) trend toward higher inequality, with SSP4 distinguished by especially high within-country inequality. Divergence across SSPs is strongest for emerging economies and weakest for industrialized ones. Follow-up work (non-parametric projections of national income distributions consistent with the SSPs) extends this from Gini summary statistic to full distributional projections usable in microsimulation and IAM applications.

Building on these distributional baselines, Soergel et al. (2021) couple an IAM mitigation pathway with a poverty microsimulation to assess a 1.5°C-consistent scenario against the SDGs. They find that, absent redistribution, mitigation policy pushes an estimated 50 million additional people into poverty by 2030 via higher food and energy prices — but that recycling domestic carbon-pricing revenue as an equal per-capita dividend not only offsets this effect but produces a small net reduction in the global poverty headcount (about 6 million), directly paralleling the (Budolfson et al., 2021) finding above, while embedded in an explicit SSP/SDG-consistent baseline.

(Jafino et al., 2020) take the complementary approach of holding mitigation policy fixed and varying the SSP socioeconomic baseline to bound the poverty impact of climate change itself: running the projection under a 'pessimistic' (SSP4) versus 'optimistic' (SSP5) socioeconomic trajectory roughly halves the estimated number of people pushed into extreme poverty by climate impacts by 2030 (32–132 million across scenarios), with food-price and health-channel effects dominating, especially in Sub-Saharan Africa. This illustrates that the socioeconomic baseline — i.e., which SSP is assumed — can matter as much for poverty outcomes as the mitigation policy itself.

Most recently, a multi-model assessment (Emmerling et al., 2024) pools eight large-scale IAMs that explicitly feature income heterogeneity, spanning different economic paradigms, to jointly assess climate change and inequality within a consistent SSP-based framework. This work finds that (i) unmitigated climate impacts raise the global Gini index by about 1.4 points on average by 2100, (ii) holding warming below 1.5°C cuts this long-run inequality increase by roughly two-thirds (at a small, temporary short-term cost), and (iii) the redistributive design of carbon-revenue use is what ultimately determines whether mitigation reduces or exacerbates inequality.

In general, four main conclusions can be drawn across this literature which are directly relevant to modelling household heterogeneity within a mitigation-pathway framework:

- The sign of the distributional impact is ambiguous. Whether carbon pricing is regressive or progressive depends on the income concept (annual vs. lifetime), on the country income level, as well as on the shape of the energy-expenditure–income relationship and not so much on carbon pricing per se.
- Models should avoid importing an OECD-derived regressivity assumption into contexts (e.g., lower-income regions or countries) where the underlying energy-access pattern differs.

- Partial-equilibrium expenditure incidence understates the true distributional footprint. Employment and income channels (Känzig, 2023) mainly account for the aggregate household impact, arguing for household-heterogeneity modules linked to a full general-equilibrium (or at least labour-market) representation rather than static expenditure incidence alone.
- Revenue-recycling design dominates the direct price effect. In almost all studies reviewed, the decision how carbon-pricing revenue is used is the single largest lever on net distributional outcomes (in many cases, more than the choice of carbon price path itself).

The SSP framework already encodes distinct inequality trajectories (Rao et al., 2019) that should be treated as a modelling *input*, not an emergent output, when household heterogeneity is layered onto a mitigation pathway — and mitigation-side distributional feedbacks should in turn be assessed against that SSP-consistent baseline rather than a static income distribution.

This is one important conclusion from the literature for the design of this study. The DIAMOND household dataset has been used as an input for the SSP scenarios modelled in GCAM-Europe, and the result of this exercise shows the relevance of the dynamics in income distribution on mitigation pathways. A specific result there is the heterogeneity across EU countries, given the distributional heterogeneity and different income levels, which play the most important role for energy demand feedbacks. Dynamic interaction between mitigation pathways and the implemented policies depend on the reactions of different household types at different income levels. This result is also corroborated by the second application of the DIAMOND household dataset in the NEMESIS model. It is shown that the characteristics of different datasets in terms of income distribution can drive important differences in results of the burden of carbon pricing.

3.3 Scenario analysis with GCAM-Europe and income distribution

GCAM-Europe, as well as GCAM, relies on an extensive exogenous sociodemographic dataset, which is one of the main drivers for sectoral demand across energy, food, and buildings. Recent methodological advancements now enable the disaggregation of this data into regional household deciles, allowing for highly nuanced representation of demand heterogeneity.

Leveraging this capability, we model three distinct household income distribution scenarios up to 2050. Across all three scenarios, total regional GDP and population remain constant for both historical and projected timeframes. Instead, the income deciles are dynamically adjusted to reflect the narratives of the Shared Socioeconomic Pathways (SSPs). Specifically, we explore SSP1 –a shift toward a more egalitarian world–, SSP2 – the benchmark continuation of historical trends – and SSP3 – a trajectory of resurgent nationalism and regional rivalry. Upon these income distributions, we overlay the DIAMOND Baseline policy framework. The DIAMOND Baseline scenario within GCAM-Europe is specifically parameterised to reflect the European policy landscape while maintaining global modelling simplicity by aggregating non-European climate action into 11 major regional blocks.

For the EU-27, the scenario enforces explicit CO_2 targets aligned with the 2030 NECPs and long-term net-zero commitments. To accurately represent this transition, the DIAMOND Baseline integrates several targeted background policies: an EU-wide ETS-1 cap for the electricity and industry sectors up to 2030 (held constant thereafter), comprehensive vehicle efficiency standards featuring a post-2035 ban on internal combustion engines, and country-specific coal phase-out schedules. Additionally, the scenario applies realistic end-user energy taxation on electricity, gas, and transport fuels, matching actual historical values up to 2024 and fixing them for the remainder of the projection period.

To generate the sophisticated income distributions, we utilize *pridr* (https://github.com/JGCRI/pridr), an open-source R package integrated within the GCAM ecosystem. While *pridr* supports various statistical approaches, we

apply its principal component (PC) model. This model efficiently summarises a country's ten decile shares in just two components, enabling the projection of full distributions from a streamlined set of explanatory variables. Future pathways start from a 2015 country-level benchmark; for the EU27 regions, this historical baseline is explicitly substituted with the DIAMOND household data.

The PC model operates on two main drivers: The first component is driven by the Gini index, which is projected by scaling its 2015 values using SSP-specific factors derived from (Rao et al., 2019). The second component relies on the labour share of income (the proportion of national income paid to workers as wages, salaries and benefits), alongside the lagged income share of the ninth decile and the lagged Palma ratio (the income share of the richest 10% divided by that of the poorest 40%). These variables are held constant at their 2015 level; consequently, future distributions are primarily driven by the evolution of the Gini index applied against this historical baseline. Finally, these country-level projections are aggregated into GCAM-Europe regions using population and GDP per capita data specific to each SSP. Within each region, population segments from all constituent countries are pooled and ranked from poorest to richest based on per-capita income. They are then dynamically regrouped into ten regional deciles using cumulative 10% population thresholds. If a country's population segment straddles a threshold, it is proportionally split so that every regional decile contains exactly 10% of the population. Ultimately, the regional income shares and Gini coefficients are calculated from the GDP of these newly assembled segments using population weights.

In GCAM-Europe, the demand for key services such as residential floorspace, residential energy, and food, is computed at the household group level, which consequently drives corresponding emissions. In particular, residential floorspace is estimated using a Gompertz function; therefore, altering the income of each group directly modulates both the decile-specific floorspace demand and the aggregate regional total. Building on this, residential energy services and fuel consumption are governed by group income, floorspace availability, and additional exogenous and endogenous drivers. Consequently, shifts in income and floorspace distribution directly alter energy service demand, subsequently impacting fuel consumption and regional totals. Depending on the scenario, these dynamics also dictate the rate at which low- and high-income cohorts reach energy satiation, generating knock-on effects on final energy demand and the overall fuel mix.

While food demand can similarly be calibrated by consumer group, propagating income distribution changes through agricultural demand, land use, commodity prices, and land-use emissions, the DIAMOND Baseline scenario represents food demand solely at the regional level. As a result, income distribution does not influence food dynamics in this specific exercise.

The dynamics in income growth by decile drives the demand for floorspace which in turn determines energy services and fuel demand (by fuel type). This drives the observed heterogeneity in the difference of energy demand and emissions across EU-countries between scenarios. In general, this heterogeneity is smaller for energy demand than for emissions. Comparing SSP2 and SSP3 with SSP1 shows that some countries (e.g., Germany and Spain) show considerably lower energy and emission results, whereas other show almost no difference or even positive values. The unweighted aggregate difference in residential energy demand (2050) is –0.5% between SSP2 and SSP1 and –0.4% between SSP2 and SSP1. For emissions, the difference is even positive, due to some high outlier values.

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Table 3.1. Residential Final Energy Demand, difference between SSP2 and SSP1

	2030	2035	2040	2045	2050
Austria	0.02%	0.01%	0.01%	0.02%	-0.01%
Belgium	-0.01%	-0.03%	-0.04%	-0.05%	-0.09%
Bulgaria	-0.25%	-0.39%	-0.71%	-1.23%	-1.92%
Croatia	-0.01%	-0.01%	-0.01%	-0.04%	-0.10%
Cyprus	-0.13%	-0.17%	-0.20%	-0.25%	-0.32%
Czech Republic	-0.07%	-0.04%	0.08%	0.41%	0.65%
Denmark	-0.03%	-0.06%	-0.08%	-0.11%	-0.14%
Estonia	-0.13%	-0.20%	-0.27%	-0.30%	-0.34%
Finland	0.00%	-0.02%	-0.04%	-0.05%	-0.06%
France	-0.01%	-0.03%	-0.06%	-0.11%	-0.17%
Germany	-0.15%	-0.36%	-0.58%	-0.85%	-1.14%
Greece	0.00%	-0.02%	-0.06%	-0.12%	-0.21%
Hungary	-0.03%	-0.07%	-0.10%	-0.15%	-0.35%
Ireland	-0.10%	-0.18%	-0.28%	-0.38%	-0.49%
Italy	0.01%	0.01%	-0.01%	-0.06%	-0.15%
Latvia	-0.06%	-0.11%	-0.17%	-0.28%	-0.49%
Lithuania	-0.31%	-0.43%	-0.67%	-1.23%	-1.53%
Luxembourg	-0.02%	-0.03%	-0.04%	-0.05%	-0.06%
Malta	-0.20%	-0.36%	-0.56%	-0.78%	-1.01%
Netherlands	-0.11%	-0.21%	-0.36%	-0.53%	-0.68%
Poland	-0.25%	-0.03%	0.12%	0.26%	-0.14%
Portugal	-0.13%	-0.26%	-0.38%	-0.51%	-0.64%
Romania	0.03%	-0.04%	-0.17%	-0.33%	-0.92%
Slovakia	-0.18%	-0.39%	-0.74%	-0.96%	-1.52%
Slovenia	-0.04%	-0.08%	-0.12%	-0.18%	-0.26%
Spain	-0.08%	-0.14%	-0.27%	-0.42%	-0.60%
Sweden	0.00%	0.00%	-0.02%	-0.04%	-0.07%

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Table 3.2. Residential Final Energy Demand, difference between SSP3 and SSP1

	2030	2035	2040	2045	2050
Austria	0.06%	0.08%	0.10%	0.10%	0.10%
Belgium	0.00%	-0.02%	-0.02%	-0.05%	-0.11%
Bulgaria	-0.18%	-0.23%	0.38%	-0.36%	0.36%
Croatia	0.02%	0.00%	-0.04%	-0.10%	-0.22%
Cyprus	-0.10%	-0.22%	-0.39%	-0.52%	-0.69%
Czech Republic	0.02%	0.01%	0.11%	0.13%	0.47%
Denmark	-0.01%	-0.04%	-0.09%	-0.17%	-0.29%
Estonia	-0.19%	-0.36%	-0.55%	-0.75%	-0.97%
Finland	0.03%	0.02%	0.02%	0.03%	0.02%
France	-0.03%	-0.07%	-0.12%	-0.19%	-0.30%
Germany	-0.15%	-0.37%	-0.59%	-0.81%	-1.04%
Greece	-0.05%	-0.11%	-0.17%	-0.23%	-0.34%
Hungary	0.01%	0.01%	0.00%	-0.03%	-0.07%
Ireland	-0.18%	-0.33%	-0.49%	-0.67%	-0.86%
Italy	0.01%	0.00%	-0.04%	-0.11%	-0.26%
Latvia	-0.05%	-0.06%	-0.07%	-0.11%	-0.16%
Lithuania	-0.22%	-0.28%	-0.50%	-0.69%	-0.64%
Luxembourg	-0.11%	-0.21%	-0.30%	-0.39%	-0.53%
Malta	-0.22%	-0.40%	-0.63%	-0.89%	-1.19%
Netherlands	-0.15%	-0.29%	-0.51%	-0.75%	-0.98%
Poland	-0.16%	-0.01%	0.20%	-0.03%	0.30%
Portugal	-0.16%	-0.30%	-0.42%	-0.57%	-0.73%
Romania	0.06%	0.08%	-0.09%	-0.18%	-0.29%
Slovakia	-0.04%	-0.04%	-0.05%	-0.08%	-0.12%
Slovenia	-0.05%	-0.10%	-0.15%	-0.22%	-0.31%
Spain	-0.19%	-0.37%	-0.58%	-0.80%	-1.11%
Sweden	0.01%	0.00%	-0.01%	-0.03%	-0.05%

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Table 3.3. Residential CO_2 emissions, difference between SSP2 and SSP1

	2030	2035	2040	2045	2050
Austria	0.03%	0.01%	-0.01%	0.28%	0.17%
Belgium	0.00%	-0.02%	-0.09%	-0.06%	0.00%
Bulgaria	-0.03%	-0.03%	-0.12%	-0.09%	-0.57%
Croatia	-0.02%	-0.05%	-0.02%	-0.10%	-0.14%
Cyprus	-0.16%	-0.22%	-0.29%	-0.35%	-0.52%
Czech Republic	-0.31%	-0.07%	0.76%	3.81%	8.10%
Denmark	-0.04%	-0.07%	-0.11%	-0.19%	-0.25%
Estonia	-0.14%	-0.19%	-0.25%	-0.33%	-0.33%
Finland	-0.05%	-0.07%	-0.02%	0.04%	0.93%
France	0.00%	-0.02%	-0.06%	-0.10%	-0.16%
Germany	-0.14%	-0.29%	-0.51%	-0.87%	-1.36%
Greece	0.04%	0.03%	-0.06%	-0.10%	0.04%
Hungary	0.01%	-0.02%	0.07%	0.31%	0.31%
Ireland	-0.11%	-0.20%	-0.31%	-0.38%	-0.39%
Italy	0.01%	-0.03%	-0.07%	-0.15%	-0.25%
Latvia	-0.01%	-0.12%	0.55%	-0.20%	-0.38%
Lithuania	-0.25%	0.53%	1.51%	-0.73%	1.58%
Luxembourg	-0.01%	-0.10%	-0.16%	-0.24%	-0.17%
Malta	0.55%	0.38%	0.33%	0.31%	0.81%
Netherlands	-0.12%	-0.22%	-0.53%	-0.75%	-0.95%
Poland	-0.17%	1.37%	3.61%	6.75%	7.23%
Portugal	-0.18%	-0.43%	-0.69%	-1.10%	-1.70%
Romania	0.03%	-0.05%	-0.04%	-0.21%	-0.96%
Slovakia	-0.09%	-0.18%	-0.42%	1.65%	1.57%
Slovenia	0.00%	-0.04%	-0.10%	-0.19%	-0.28%
Spain	-0.09%	0.07%	-0.37%	-0.57%	-0.85%
Sweden	-0.05%	-0.08%	-0.10%	-0.14%	-0.19%

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Table 3.4. Residential CO_2 emissions, difference between SSP3 and SSP1

	2030	2035	2040	2045	2050
Austria	0.09%	0.08%	0.07%	0.42%	0.50%
Belgium	0.00%	-0.02%	-0.20%	-0.09%	0.10%
Bulgaria	-0.04%	-0.05%	12.31%	-0.13%	30.88%
Croatia	-0.01%	-0.12%	-0.04%	-0.08%	-0.34%
Cyprus	-0.35%	-0.48%	-0.79%	-1.01%	-1.40%
Czech Republic	-0.37%	-0.19%	1.13%	4.39%	12.84%
Denmark	-0.06%	-0.15%	-0.26%	-0.51%	-0.79%
Estonia	-0.37%	-0.56%	-0.80%	-1.08%	-0.93%
Finland	-0.09%	-0.12%	0.00%	0.93%	1.27%
France	-0.02%	-0.06%	-0.17%	-0.15%	-0.26%
Germany	-0.28%	-0.58%	-1.08%	-1.63%	-2.21%
Greece	0.12%	0.10%	-0.16%	-0.05%	0.04%
Hungary	0.06%	0.03%	0.14%	0.35%	0.77%
Ireland	-0.30%	-0.57%	-0.85%	-1.01%	-0.99%
Italy	0.02%	-0.09%	-0.20%	-0.40%	-0.64%
Latvia	-0.05%	0.25%	0.21%	-0.28%	0.04%
Lithuania	-0.44%	0.90%	1.14%	-1.21%	5.23%
Luxembourg	-0.07%	-0.35%	-0.58%	-0.73%	-0.60%
Malta	1.14%	0.59%	0.26%	0.14%	0.92%
Netherlands	-0.29%	-0.53%	-1.28%	-1.83%	-2.31%
Poland	-0.32%	2.22%	6.39%	9.82%	14.59%
Portugal	-0.43%	-1.01%	-1.53%	-2.36%	-3.62%
Romania	0.07%	-0.02%	-0.13%	-0.46%	-1.29%
Slovakia	-0.10%	-0.25%	-0.52%	1.51%	1.41%
Slovenia	-0.02%	-0.10%	-0.25%	-0.44%	-0.64%
Spain	-0.25%	-0.34%	-1.09%	-1.18%	-2.01%
Sweden	-0.14%	-0.18%	-0.21%	-0.28%	-0.45%

3.4 Scenario analysis with NEMESIS and income distribution

To introduce household heterogeneity into the NEMESIS model, two alternative datasets were used: Eurostat and DIAMOND. Both provide information on household income and consumption expenditure by income decile across European countries, allowing the distribution of economic resources and expenditure patterns to be represented within the model.

The Eurostat dataset originates from the European project on income, consumption and wealth inequalities (ICW). It combines microdata from the European Union Statistics on Income and Living Conditions (EU-SILC) and Household Budget Survey (HBS) with national accounts through statistical reconciliation procedures (Eurostat, 2024). The DIAMOND dataset developed within the DIAMOND project, also draws on EU-SILC and HBS data but relies on a two-stage statistical matching procedure to construct a synthetic dataset combining household income and consumption information (Kratena et al., 2021). Although both datasets cover comparable dimensions, they differ in their construction methods, level of disaggregation and coverage of income and consumption categories. Further details on their characteristics, processing and differences are provided in Deliverable 4.3.

Figure 3.1 and Figure 3.2 show the share of each household decile in each income and consumption category,

based on raw Eurostat (right) and DIAMOND data (left). In these figures, Belgium, France, Germany, and Spain are used as examples to illustrate the differences in the distribution of income and households' consumption across decile depending on the data source considered.

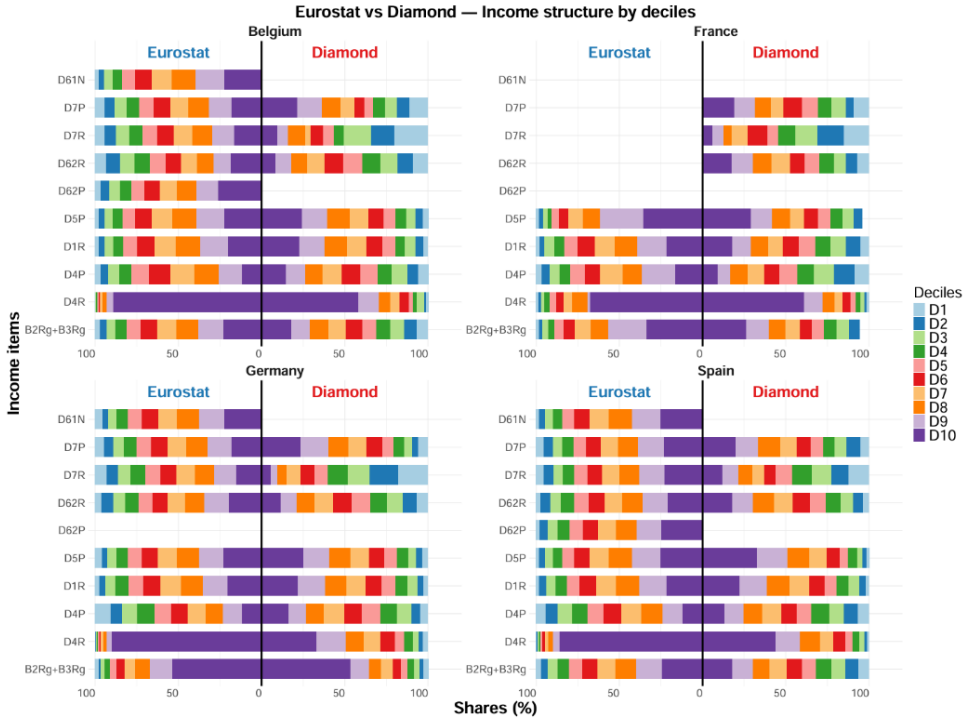

Figure 3.1. Eurostat vs. DIAMOND: distribution of household income components across deciles (Belgium, France, Germany and Spain)

Source: authors' calculation based on Eurostat and DIAMOND dataset.

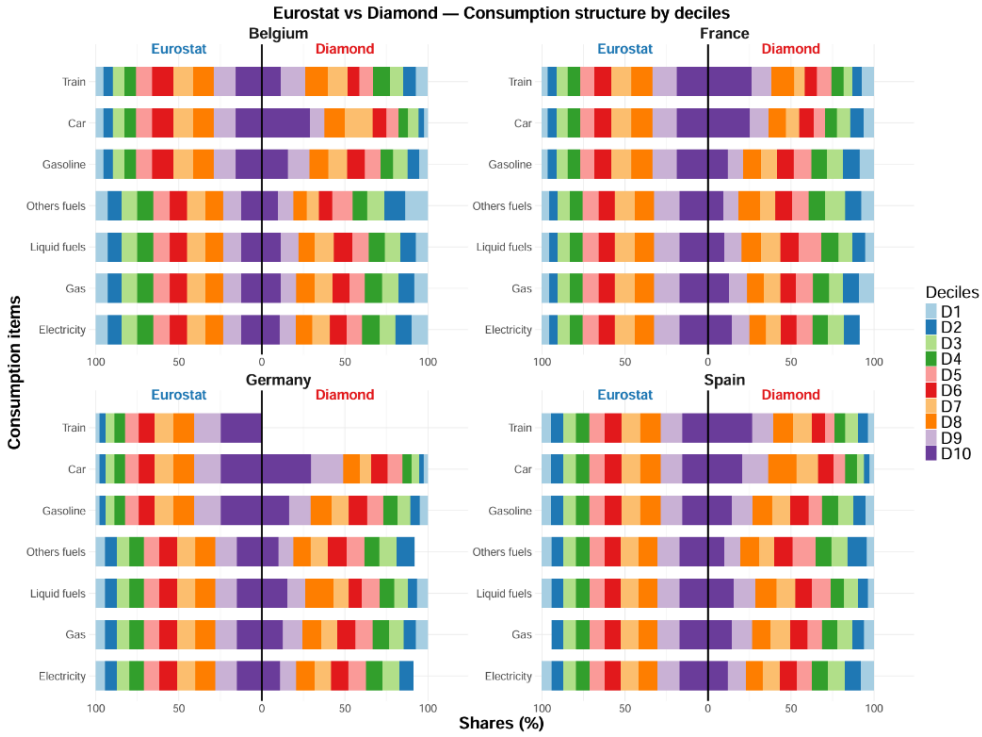

Figure 3.2. Eurostat vs. DIAMOND: distribution of household consumption components across deciles (Belgium, France, Germany and Spain)

Source: authors' calculation based on Eurostat and DIAMOND dataset.

To incorporate these data into NEMESIS, the income and consumption categories of each dataset are first mapped to the corresponding variables of the model. For each category and country, the share attributable to each income decile is then calculated and applied to the corresponding aggregate household variable. This procedure enables the disaggregation of the representative household into ten income groups, each with its own income components and consumption structure. The household module's equations are subsequently extended to represent these groups, allowing their income and consumption to evolve within the dynamic macroeconomic framework while preserving consistency with aggregate model variables. A detailed description of the NEMESIS household module and the data integration procedure is available in Deliverable 4.3.

3.4.1 Carbon pricing scenarios in NEMESIS

The disaggregation of households by income decile in NEMESIS makes it possible to assess how climate policies affect households differently depending on their position in the income distribution. By capturing differences in income sources, consumption patterns and behavioural responses, this extended framework provides insights into the distributional consequences of climate policies and can help inform the design of measures that account for their heterogeneous impacts.

To illustrate these capabilities, we simulate the introduction of an increasing carbon price across the European Union over the 2025–2060 period. Two climate policy scenarios are considered. In the baseline scenario, carbon prices remain constant at their 2025 levels, based on the European Energy Exchange for the EU Emissions Trading System (EU ETS) and the World Bank Carbon Pricing Dashboard for existing national carbon pricing mechanisms outside the EU ETS.[10] In the carbon pricing scenario, a progressively increasing carbon price is introduced, starting at €73/tCO_2 in 2025 and reaching €138/tCO_2 in 2030, €352/tCO_2 in 2040, €854/tCO_2 in 2050 and €1,510/tCO_2 in 2060, based on the trajectories considered by (Chang and Harrison, 2025) and the (European Commission, 2024). Where an existing national carbon price exceeds the simulated trajectory, the higher national price is maintained.

The carbon pricing scenario is implemented using both the Eurostat and DIAMOND datasets, resulting in two simulations, *CP_Euro* and *CP_Diam*, respectively. Both incorporate the income and consumption channels differentiated by household decile, together with decile-specific price and income elasticities to account for heterogeneous consumption responses. No carbon revenue recycling mechanism is introduced, allowing the analysis to focus on the effects of carbon pricing on household disposable income and consumption in the absence of compensatory transfers. The outcomes are assessed relative to the corresponding baseline simulations over the 2025–2060 period.

Building on the scenarios presented above, this section examines the effects of increasing carbon prices on household disposable income and consumption across income deciles, focusing primarily on the DIAMOND-based simulation and comparing its results with those obtained using Eurostat data. The results in Figure 3.3 and Figure 3.4 are presented at EU level.

[10] World Bank website, States and Trends of Carbon Pricing

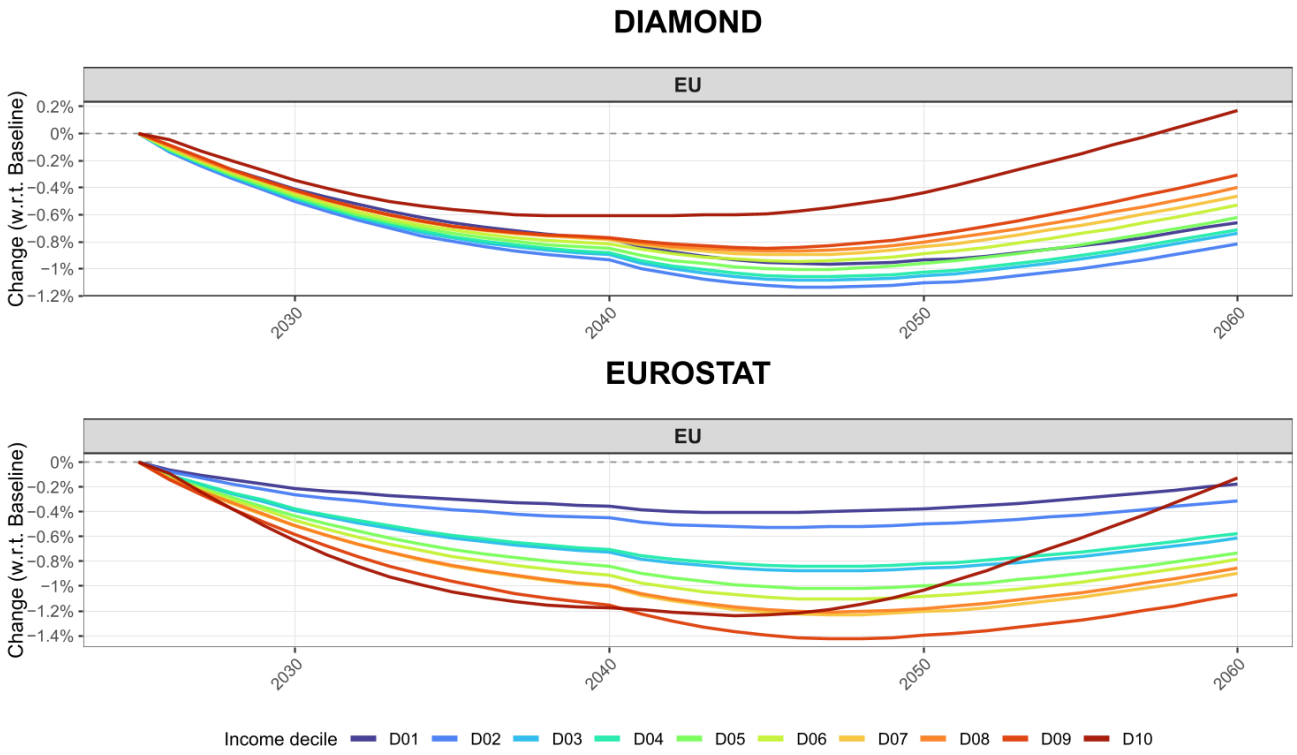

Figure 3.3. Change in disposable income by households decile at EU level: *"Baseline"* vs *"CP_Diam" and "CP_Euro"*
"CP_Euro" and "CP_Diam" scenarios correspond to the increasing carbon pricing.

The carbon pricing scenario based on the DIAMOND dataset (*CP_Diam*) leads to a reduction in household disposable income across almost all income deciles over the simulation period (Figure 3.3). Income losses generally increase until 2045, before gradually diminishing towards 2060. However, their magnitude differs across income groups, with lower-income deciles generally experiencing larger proportional income losses, while the highest-income decile (D10) experiences the smallest losses and records a modest gain relative to the baseline by 2060.

3.4.2 Income and carbon burden in the carbon pricing scenarios

The decomposition of disposable income changes reveals that the decline in compensation of employees (D1R) constitutes the main negative contribution across all deciles (Figure 3.4). At the macroeconomic level, this reflects a combination of moderate employment reductions in major economic sectors and nominal wage growth that remains below consumer price inflation, resulting in lower real labour income. These losses are partially offset by positive contributions particularly from net social contributions (D61N). This mainly results from a price-deflator effect: nominal social contributions paid by households increase with the wage bill but less rapidly than consumer prices, reducing their real burden. This effect therefore does not necessarily reflect additional social redistribution. Net property income (D4N) also contributes negatively, particularly for D10. Although aggregate nominal property income increases through adjustments in investment prices, capital stocks and interest rates, its growth remains below consumer price inflation, leading to a decline in real terms. Its greater contribution for D10 mainly reflects the concentration of property income among higher-income households.

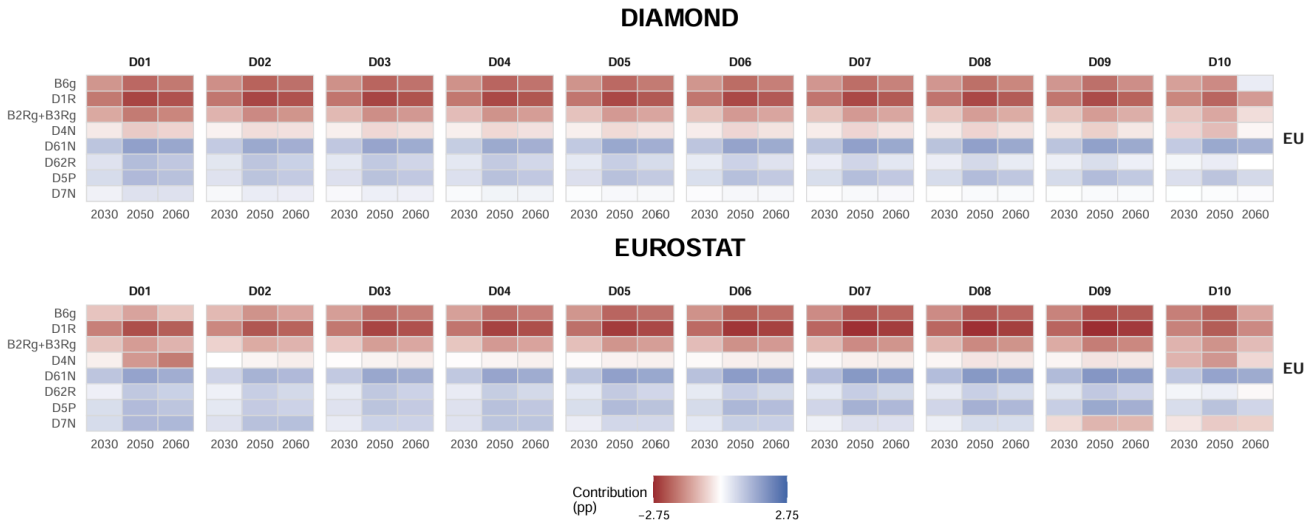

Figure 3.4. Contribution of the income' components to change in disposable income at EU level: *"Baseline"* vs *"CP_Diam"* and *"CP_Euro"*

"CP_Euro" and "CP_Diam" scenarios correspond to the increasing carbon pricing. B6g: Disposable income; D1R: Compensation of employees; B2Rg+B3Rg: Operating surplus and mixed income, gross; D61N: Net social contributions; D5P: Current taxes on income and wealth; D7N: Other current transfers (net); D4N: Property income (net); D62R: Social benefits, other than social transfers in kinds (STiK).

Using the Eurostat dataset (*CP_Euro*) produces a different distribution of income losses (Figure 3.3). While disposable income follows a broadly similar temporal pattern, the largest declines are now generally observed among higher-income deciles. In 2045, D01 experiences a reduction of 0.41%, compared with 1.40% for D09 and 1.24% for D10. The latter also exhibits a strong recovery towards 2060, although its disposable income remains slightly below the baseline (−0.13%). The decomposition of income changes reveals similar macroeconomic transmission channels (Figure 3.4). However, their relative importance differs across deciles, reflecting differences in the initial distribution of income components between the two datasets, particularly wages, operating surplus and property income, as well as their distribution across countries.

These contrasting patterns are reflected in the evolution of income inequality and tax progressivity (Table 3.5). Under *CP_Diam*, the Reynolds–Smolensky index, which measures the redistributive effect of carbon pricing on income inequality (positive values indicating a reduction in inequality and negative values an increase), remains negative throughout the period, declining from −0.00022 in 2030 to −0.0016 in 2060, indicating increasing inequality relative to the baseline. The Suits index, which measures the progressivity of carbon taxation relative to income (with positive values indicating a progressive tax burden and negative values a regressive one), also remains negative (−0.023 in 2030 and −0.018 in 2060), indicating a persistently regressive carbon burden. With Eurostat, the Reynolds–Smolensky index is also negative between 2030 and 2050, reaching −0.00116 in 2040, before turning slightly positive in 2060 (+0.00035), suggesting a modest reduction in inequality at the end of the simulation period. Meanwhile, the Suits index shifts from negative in 2030 (−0.044) to positive in 2040 (+0.019), reaching +0.071 in 2060, indicating an increasingly progressive distribution of the carbon burden. These differences illustrate how the choice of household data can substantially influence the assessment of carbon pricing's distributive effects. The uncertainty in the choice of the household dataset can be reduced by decomposing it into 'real data issues' (like the baseyear, sources used, etc.) and the adjustment of the raw data to the macroeconomically balanced dataset that meets the constraints and conditions of the model (in this case NEMESIS) applied.

Table 3.5. Income inequality and regressivity indexes for EU in "CP_Diam" and "CP_Euro" scenarios with respect to the "Baseline".

Datasets	Indicators	2030	2040	2050	2060
DIAMOND *CP_Diam*	Reynolds-Smolensky	-0,00022	-0,00047	-0,0011	-0,0016
	Suits	-0,023	-0,012	-0,007	-0,018
Eurostat *CP_Euro*	Reynolds-Smolensky	-0,00061	-0,00116	-0,00082	0,00035
	Suits	-0,044	0,019	0,067	0,071

"CP_Euro" and "CP_Diam" scenarios correspond to the increasing carbon pricing scenario.

Beyond the effects on disposable income, carbon pricing also influences household consumption patterns and budget constraints.

The carbon pricing scenario based on DIAMOND data (*CP_Diam*) leads to substantial changes in household energy consumption expenditure, with differentiated responses across income deciles (Figure 3.5). Relative to the baseline, expenditures on gas and liquid fuels decline considerably for all households, with larger relative reductions among higher-income deciles. By 2060, gas expenditure decreases by 59.6% for D01 and 80.0% for D10, while liquid fuels expenditure falls by 73.7% and 87.3%, respectively. Gasoline also records substantial reductions, although differences across deciles are less pronounced (−40.0% for D01 and −43.2% for D10 in 2060). Conversely, electricity expenditure (06) increases markedly among higher-income households, reaching +59.3% for D10 in 2060, compared with a slight decline of 1.8% for D01. These contrasting developments are consistent with a stronger shift towards electricity among higher-income households, while lower-income groups exhibit more limited adjustments.

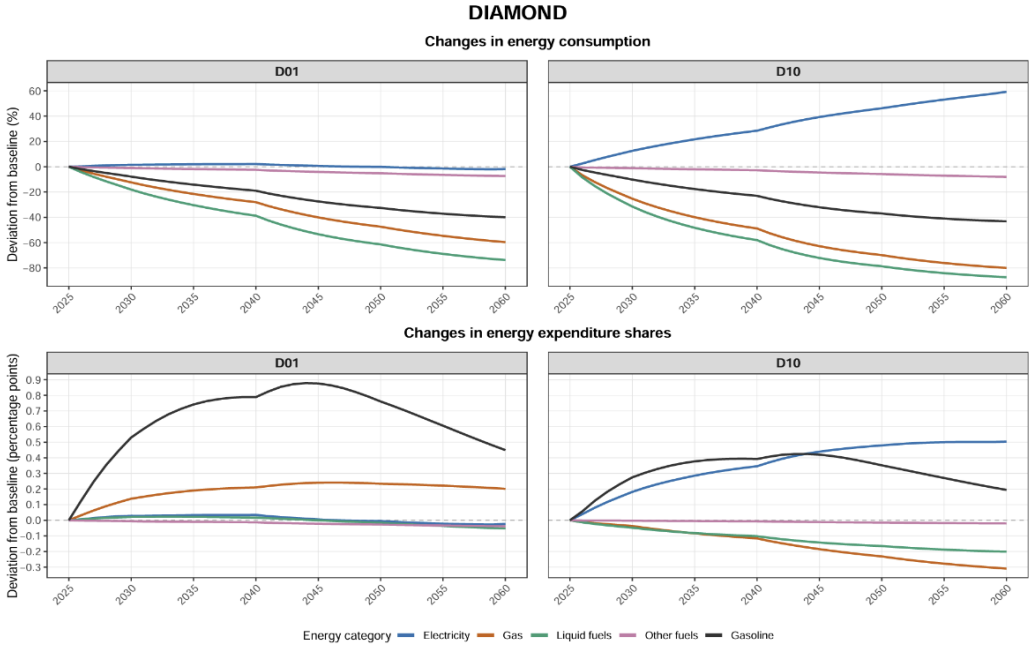

Figure 3.5. Change in energy consumption (in constant prices) and in energy expenditure shares (in current prices) compared to the "Baseline" scenario for deciles D01 and D10 for the EU under scenarios: *"CP_Diam"*

"CP_Diam" scenarios correspond to the increasing carbon pricing.

Despite these changes, carbon pricing increases the relative weight of several energy expenditures in household

budgets compared with the baseline (Figure 3.5). In particular, the budget share devoted to gasoline rises across all deciles, reaching 5% for D01 in 2040 compared with 4.2% in the baseline, against 3.5% and 3.1%, respectively, for D10. The share of gas expenditure also increases for lower-income households while declining for higher-income groups, whereas electricity exhibits the opposite pattern. Overall, considering the five energy categories, their combined budget share in 2040 increases from 8.4% to 9.5% for D01, compared with an increase from 5.8% to 6.3% for D10. Although energy expenditure shares decline over time in both scenarios, these results indicate that carbon pricing places a greater additional pressure on the consumption budget of lower-income households. Broadly similar qualitative patterns are observed with the Eurostat-based specification (*CP_Euro*).

Although energy expenditure shares decline over time in both scenarios, carbon pricing places greater additional pressure on the consumption budgets of lower-income households. Importantly, differences across deciles concern not only the direction but also the magnitude of consumption adjustments. Higher-income households, particularly D10, exhibit substantially stronger shifts in electricity, gas and liquid fuels expenditure, whereas adjustments remain much more limited for D01. These results are consistent with a greater capacity among higher-income households to adapt their energy consumption patterns, while lower-income households face stronger constraints. Broadly similar patterns are observed with the Eurostat-based specification (CP_Euro).

The Budget Burden indicator, defined as the share of carbon tax payments in total household consumption expenditure, further highlights the unequal distribution of the carbon pricing burden across income deciles (Figure 3.6). Under CP_Diam, the burden decreases systematically with income, representing 1.68% of total expenditure for D01 in 2030, compared with only 0.56% for D10. It reaches a maximum around 2040–2045 before progressively declining towards 2060, despite the continued increase in carbon prices, consistent with households' adjustments in energy consumption. Nevertheless, substantial differences persist across income groups, with the burden reaching 1.14% for D01 in 2060, compared with 0.42% for D10. These results highlight the regressive nature of the carbon pricing burden, reflecting both differences in consumption structures and the more limited capacity of lower-income households to adjust their energy demand.

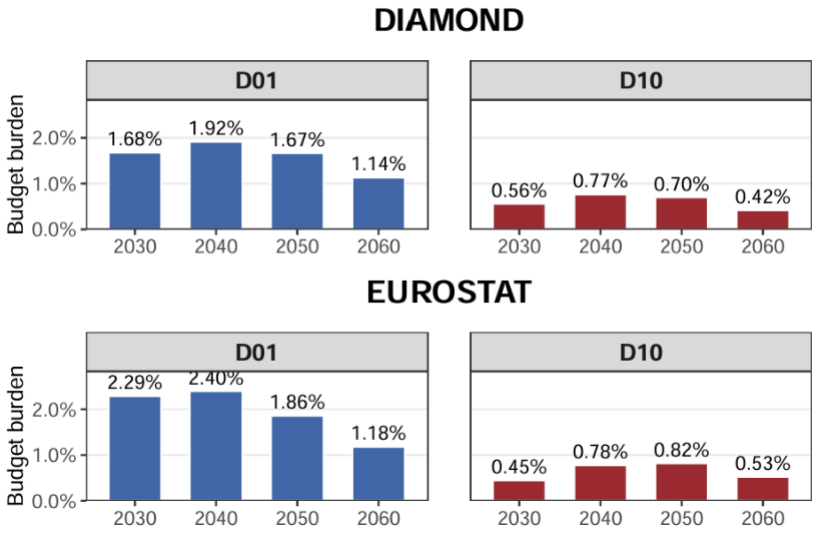

Figure 3.6. The Budget Burden indicator for deciles D01 and D10 for EU under *"CP_Diam"*

"CP_Diam" scenarios correspond to the increasing carbon pricing.

3.5 Conclusions

This study focuses on the integration of household datasets into existing IAMs in order to analyse feedbacks between mitigation policies, mitigation paths and income distribution. For this purpose, the DIAMOND household

data set has been integrated into the GCAM-Europe model and both the DIAMOND household data set and an alternative dataset based on EUROSTAT have been integrated into the NEMESIS model.

A literature review reveals that household heterogeneity has already been integrated into IAMs in the context of SSP scenario analysis. One important result was that general equilibrium feedbacks and the impacts of climate change on different income levels play an import role in the evaluation of mitigation policies and pathways. This study explores the direct energy and emission feedbacks (not only general equilibrium) from income distribution and shows how results with models that include behavioural household heterogeneity can differ in their results for different datasets of household heterogeneity.

In model simulations with GCAM-Europe, shifts in income by household type have an impact on residential energy demand via different channels of mechanisms. One is a saturation effect in the demand for floorspace, and the other one is an income dependent energy service demand. These two mechanisms work for different income levels and distributions across countries and in the different SSP scenarios produce large heterogeneity in energy and emission results. In the model simulations with NEMESIS, where households exhibit differentiated behavioural responses across income deciles, a detailed assessment of the distributional effects of climate policies is carried out. These carbon pricing simulations demonstrate the relevance of household heterogeneity, revealing substantial differences across income groups in disposable income changes, energy consumption adjustments and budgetary burdens. Lower-income households generally face greater constraints, while higher-income households exhibit stronger consumption adjustments. Furthermore, differences between the Eurostat- and DIAMOND-based results highlight the sensitivity of the results to the initial data selection to calibrate the model.

Overall, these developments strengthen the capacity of the two selected IAMs (GCAM-Europe and NEMESIS) to analyse the interdependence of emission mitigation and income distribution and the relevant heterogeneity in results across countries and household groups. The simulations with the IAMs demonstrate the consequences of climate policies as well as other policies impacting consumption and income channels and provide a foundation to frame policy measures that better account for differences in household circumstances.

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4 The implications of labour market and financial dynamics, and consumer behaviour for climate policy

4.1 Introduction

4.1.1 Frictions and heterogeneity in the transition

Decarbonisation requires workers to move from contracting to expanding sectors. It requires investing firms to finance new technologies. It requires households to replace the durables they use for heating and mobility. Each of these adjustments takes place in a market with frictions. Workers face search and job displacement costs and skill mismatch. Investing firms face financing costs that depend on technology maturity and on access to financial instruments. Households face affordability constraints and learn about new technologies mainly from people with incomes similar to their own. These frictions affect the speed of the transition, its cost and the distribution of that cost across workers, firms and households.

4.1.2 Representation in integrated assessment models

Sanders et al. (2026) survey eleven process-based IAMs, including five DIAMOND models. Their review shows that most of these models still assume homogeneous and frictionless labour markets, uniform or exogenous costs of capital and technology choice by a cost-minimising representative agent. Under these assumptions, the policy instruments a model can assess are limited mostly to prices, such as carbon taxes and subsidies. Frictions are assumed away and instruments that act on these frictions can simply not be represented. Examples are skills certification, State Investment Bank lending or subsidies targeted at low-income households.

DIAMOND Deliverable D4.5 presented three modules that address these gaps. Each module introduces heterogeneity on the demand or supply side of one market and endogenises the matching process in that market. The labour module adds directed search to the GEMINI-E3 EU model (O'Connell et al., 2026). The finance module derives technology- and country-specific weighted average costs of capital (WACCs) that change with technology maturity, for use with the EU part of the macro-econometric model NEMESIS, and differentiated WACCs for use with CLEWs-EU (Serebriakova et al., 2026). The consumer module (HATT) models heating technology adoption by income decile with affordability constraints and locally biased information, linked to GCAM-Europe (Morley et al., 2026).

This chapter reports the policy simulations carried out with these modules.

4.1.3 Focus of this chapter

This chapter addresses two research questions.

1. How do labour market frictions, financing conditions and heterogeneous consumer behaviour change projected transition pathways and their distributional outcomes?
2. Which policy instruments act on these frictions?

The three strands are at different stages. The labour strand reports the effects of labour mobility for fourteen EU regions and illustrates the labour market policies for Germany. The finance strand reports policy results from the module that have not yet been iterated with NEMESIS to a consistent solution, as well as results from the differentiated WACCs integrated into CLEWs-EU. The consumer strand reports baseline results from an iterative soft link with GCAM-Europe, together with one policy scenario, a carbon tax combined with a heat pump subsidy

targeted by income. We report results as they stand in the working paper versions listed in Section 4.6. Updated versions of these underlying working papers will be made available here and in the final scientific articles to be submitted for peer review.

4.1.4 Structure of the chapter

Section 4.2 describes the overarching approach, the modules and the scenario design. Section 4.3 presents the results for each strand. Section 4.4 discusses the results across strands and their limitations. Section 4.5 concludes.

4.2 Study design

4.2.1 Overarching approach

Each module is soft-linked to its host model. In all three cases the module takes inputs from the host model and returns outputs that the host model can use or that complement its results. The consumer strand goes furthest. HATT and GCAM-Europe are iteratively run in turn until the energy prices in GCAM-Europe converge, so that heating technology choices and energy prices are mutually consistent. This has so far been done for the no-policy baseline; for the policy runs this work is ongoing. The labour and finance modules take the results of their host models as given. Second-round general equilibrium feedbacks are not captured. The effects of, for example, unemployment on aggregate demand or of capacity expansion on energy prices are not yet modelled. At a higher level of abstraction, the three modules all share the same structure. Each represents heterogeneous agents in the relevant market, specifies a matching process between demand and supply, and runs simulations with a set of parameters that a policy instrument can change. A policy is then simulated by changing the parameter that an instrument would act on. Each strand compares a reference run with runs in which one or more such parameters are changed.

4.2.2 Modules and host models

The labour module is a directed search model with Diamond-Mortensen-Pissarides matching frictions and Nash wage bargaining. In such a model, unemployed workers and vacancies meet through a matching function, so that unemployment and unfilled vacancies coexist, and wages are set by bargaining between worker and firm over the surplus of a match. Unemployed workers choose in which sectoral sub-market to search with a logit rule based on expected wages, job-finding probabilities and switching costs (O'Connell et al., 2026). GEMINI-E3 EU represents imperfect labour mobility through constant elasticity of transformation (CET) functions. It still assumes full employment. The module takes the wage and employment paths from GEMINI-E3 EU and inverts the wage equation and the job-creation condition. This way the soft-linked module recovers unemployment, vacancies, job-finding rates and spell durations by sector and skill. The job-finding and vacancy-filling rates are bounded at one per quarter, as the module's discrete-time formulation requires. These outcomes are not yet fed back into GEMINI-E3 EU. Closing the loop would require one additional GEMINI-E3 EU runs, mapping our policies also to the CET elasticity of the node it acts on (O'Connell et al., 2026). This, however, would require careful calibration of policy to CET-elasticities that is beyond the scope of our project.

The finance module assigns each of 15 electricity generation technologies in each country and year a normalised maturity score between 0 and 100, and this maturity determines which of six financial instruments a technology can access. The score is an average based on the technology's share in the EU energy mix and on domestic installed capacity (Serebriakova et al., 2026). The instruments are venture capital and private equity, State Investment Bank (SIB) loans, private bank loans, stocks, bonds and retained earnings. Each instrument carries a financing cost, built from the risk-free rate, country, equity and technology risk premia and lenders' margins, and a transaction cost

that falls with maturity (for SIB loans it rises beyond a mandate cut-off). Capital expenditure is allocated across eligible instruments, with larger shares going to cheaper instruments. The supply of each instrument is limited. Total energy-sector financing is set at 14% of the investment share of GDP in NEMESIS and split across instruments using shares from the literature, for example 35% for private bank loans, 30% for retained earnings and 8% for SIB loans. When demand for an instrument exceeds supply, requests are scaled down and the remainder is reallocated to other instruments. The WACC per technology, country and year is the average cost of the resulting financing mix, in which each instrument's cost is weighted by its share in the mix, with a tax shield applied to debt instruments.

Table 4.1. Modules, frictions and links to host models

Strand	Module	Friction represented	Host model	Link type	Policy levers
Labour markets	Directed search module with Diamond-Mortensen-Pissarides matching and Nash wage bargaining; unemployed workers choose the sector in which to search with a logit rule	Search frictions and imperfect transferability of skills between contracting (brown) and expanding (green) power sectors; imperfect labour mobility in the host model (nested CET)	GEMINI-E3 EU (CGE)	One-way soft link: the module inverts the wage and employment paths of GEMINI-E3 EU to recover unemployment, vacancies and durations; no feedback to the host model	Probability that a brown-origin applicant is hired in green (skills certification) Cost of searching in green (retraining subsidy) CET elasticities (mobility regime)
Finance	Finance module deriving WACCs by electricity generation technology, country and year from a normalised maturity score and the access to and cost of six financial instruments	Financing costs and access to finance that depend on technology maturity by country; limited supply of each financial instrument	CLEWs-EU (cost optimisation) NEMESIS (macro-econometric)	CLEWs-EU: empirical WACCs replace the uniform discount rate of 7.5% NEMESIS: one-way soft link; the module takes installed capacity and investment from NEMESIS; WACCs fed back in a first round only; iteration to a consistent solution under way	Interest rates on green loans (green preferential rates) Volume of State Investment Bank funding Bond financing available to green technologies (green QE)
Consumer behaviour	HATT: extension of FTT:Heat with heterogeneous household groups and investment constraints	Affordability constraint on up-front investment (25% of gross annual household income); locally biased information on market shares	GCAM-Europe	Iterative soft link: HATT market shares are converted into GCAM-Europe share weights, repeated until energy prices converge (no-policy baseline; ongoing for the policy runs)	Carbon tax Investment subsidy for water heat pumps, flat or targeted by income decile

Sources: O'Connell et al. (2026), Serebriakova et al. (2026), Morley et al. (2026).

In CLEWs-EU, an OSeMOSYS-based cost-optimisation model, the differentiated WACC replaces the uniform discount rate of 7.5%. The CLEWs-EU runs use empirical WACCs by country and technology from Hatton et al. (2025), averaged over 2019 to 2021. In NEMESIS, the module takes installed capacity (GW) and capital expenditure (billion euros, constant 2010 prices) by generation technology from the NEMESIS runs and returns financing mixes, WACCs and instances of funding constraints. A first round in which these WACCs are fed back into NEMESIS has been run, but the module and NEMESIS have not yet been iterated to a mutually consistent solution. This work is

under way; the results reported here are those of the first round. Nevertheless, the policy runs (first order impacts) are already informative.

The consumer module, HATT (Heterogeneous Adoption in Technology Transformation) is a consumer technology substitution module for the residential heating sector. It extends the FTT:Heat model (Knobloch et al., 2021) with heterogeneous household groups (Morley et al., 2026). Each income decile in each country is an agent with its own technology market shares and with heterogeneous investment constraints. Agents compare technology alternatives according to levelized cost to determine preferences. This is subject to a liquidity constraint, as a technology whose up-front investment cost exceeds 25% of gross annual household income is treated as unaffordable for that agent and cannot be preferred. Adoption also depends on perceived market shares with perceptions biased towards similar households, i.e. the nearest deciles. The module thus takes into account information spillovers and perceptions of risk associated with novel technologies, common features of models of innovation diffusion.

GCAM-Europe uses a multinomial logit substitution model with exogenous share weights calibrated on historical data to account for consumer non-cost preferences. HATT is itself calibrated on GCAM-Europe's historical data and projects technology market shares for all EU countries, from which the implied exogenous share weights can be imputed for use in a GCAM-Europe simulation. This procedure is iteratively repeated as necessary until the energy prices, endogenously determined in GCAM-Europe, converge. So far, this has been done for the no-policy baseline; for the policy runs this work is ongoing. The consumer strand is thus the only one in this chapter in which module and host model are iterated to a mutually consistent solution, so far for the baseline only. HATT is calibrated in two ways. Static calibration matches the technology shares in the initial stock, as in GCAM-Europe. Dynamic calibration matches recent changes in market shares.

4.2.3 Scenario design

For Labour, all runs use GEMINI-E3 EU. In the reference scenario, non-EU regions implement their nationally determined contributions and then their long-term strategies. The EU meets the targets set before the Fit-for-55 package by 2030 and continues to reduce emission intensity thereafter. In the climate policy scenario, the EU implements Fit-for-55 by 2030 and reaches net-zero emissions by 2050. ETS1 and ETS2 apply in both scenarios. Labour is perfectly mobile in the reference scenario. In the policy scenario, mobility is constrained by a nested CET structure under three regimes (rigid, central and flexible), each with its own set of elasticities. The elasticities of transformation rise from the rigid to the flexible regime. For total employment across energy, industry, services and agriculture they are 0.40, 0.75 and 1.50, and between fossil, other non-fossil and new renewable power generation 0.25, 0.50 and 0.90 (O'Connell et al., 2026). The model covers fourteen EU regions and is solved for 2017, 2023 and in five-year steps from 2030 to 2050.

Two labour market policies, skills certification and a retraining subsidy, are then simulated in the directed search module for Germany, which serves as an illustration. Germany has a large fossil-fuel power sector that contracts under all three regimes, and the module parameters are calibrated to German evidence where possible (O'Connell et al., 2026, Section 5.3). Skills certification raises the probability that a worker from the fossil-fuel ("brown") power sector who applies to a renewables ("green") employer is hired. In the reference run this probability is 0.4 for unskilled and 0.5 for skilled workers. A retraining subsidy lowers the cost of searching for a green job. In the reference run this cost is 0.35 for unskilled and 0.25 for skilled workers. Each policy is run at three levels, alone and combined, under each mobility regime. Certification closes 25, 50 or 75% of the gap to full transferability. Retraining reduces the search cost by 25, 50 or 75%. We emphasise that these levels are illustrative and not calibrated to existing programmes.

Table 4.2. Scenario design by strand

Strand	Host model	Reference scenario	Policy scenario(s)	Instruments and intensities	Geographic coverage
Labour markets	GEMINI-E3 EU	Non-EU regions follow NDCs and long-term strategies; EU meets pre-Fit-for-55 targets; ETS1 and ETS2; perfect labour mobility	Fit-for-55 by 2030 and net zero by 2050 under three mobility regimes (rigid, central, flexible), run in GEMINI-E3 EU	Skills certification closes 25, 50 or 75% of the gap to full transferability (baseline hiring probability 0.4 unskilled, 0.5 skilled) Retraining subsidy cuts the search cost by 25, 50 or 75% (baseline 0.35 unskilled, 0.25 skilled) Both combined at the same level	Mobility regimes: 14 EU regions Module and policies: Germany, as an illustration
Finance	CLEWs-EU	Uniform WACC of 7.5% (No further Action); differentiated empirical WACCs (Hatton et al., 2025) with carbon pricing, without net-zero constraint	Differentiated WACCs with net-zero commitment and green preferential interest rates	Renewable WACCs capped at the lowest values observed in the EU: 4.5% (hydro, onshore wind), 5% (biomass, solar PV), 5.5% (offshore wind), 7% (geothermal)	EU member states
Finance	NEMESIS	No (further) Action after 2021; Net Zero by 2050	State Investment Bank (SIB) and green quantitative easing (QE), both on the net-zero scenario	SIB: funding through SIBs doubled; fossil technologies excluded from SIB loans Green QE: bond financing for green technologies increased by 50%	EU member states
Consumer behaviour	GCAM-Europe with HATT	No-policy baseline, 2021 to 2050; GCAM-Europe native logit and HATT under static and dynamic calibration	Five scenarios designed: carbon tax; flat subsidy; tax with flat subsidy; targeted subsidy; tax with targeted subsidy (scenario 5 is reported in this chapter)	Carbon tax: EU ETS price plus non-ETS rates of 2 to 250 2020$ per tonne of CO2 equivalent in 2025, rising to 200 to 470 2020$ by 2050 Flat subsidy: 35% of the installation cost of water heat pumps Targeted subsidy: 50% for deciles 1 to 5, 20% for deciles 6 to 10	EU-27 member states; ten income deciles per country

Sources: O'Connell et al. (2026), Serebriakova et al. (2026), Morley et al. (2026).

For Finance, a constant WACC run is compared with a run using differentiated empirical WACCs in CLEWs-EU, with carbon pricing, with and without a net-zero constraint. In CLEWs-EU, the green preferential interest rate scenario caps WACCs for renewables at the lowest values observed across the EU. These are 4.5% for hydro and onshore wind, 5% for biomass and solar PV, 5.5% for offshore wind and 7% for geothermal. In NEMESIS, the module is applied to a No (further) Action scenario and a scenario compliant with net-zero emissions by 2050. Two finance policies are applied to the net-zero scenario. In the State Investment Bank (SIB) scenario (see Table 4.2), the funding available through SIBs is doubled and fossil fuel technologies are excluded from SIB loans. In the green quantitative easing (QE) scenario, the volume of bond financing available to green technologies is increased by 50%.

For Consumer Behaviour, we run GCAM-Europe with its native logit module and HATT under static and dynamic calibration in a no-policy baseline from 2021 to 2050. In principle, five policy scenarios can be conceptualised for simulation, with this chapter reporting on a scenario implementing a carbon tax combined with the targeted subsidy, against the baseline under dynamic calibration, with static calibration as a sensitivity test. The other four

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scenarios are considered for future research. These five scenarios are as follows:

- A carbon tax. It combines an estimate of the EU ETS price with country-specific non-ETS rates consistent with each country meeting its NECP targets in the baseline GCAM-Europe model. The non-ETS rates range from 2 to 250 2020$ per tonne of CO2 equivalent in 2025 and generally rise to between 200 and 470 2020$ by 2050.
- A flat subsidy of 35% of the installation cost of water heat pumps. Both subsidies target water heat pumps, which have the highest up-front costs (Morley et al., 2026).
- The carbon tax combined with the flat subsidy.
- A subsidy targeted by income, with a rate of 50% for the bottom five deciles and 20% for the top five deciles.
- The carbon tax combined with the targeted subsidy.

4.3 Results

4.3.1 Labour markets

4.3.1.1 Reference results and labour mobility

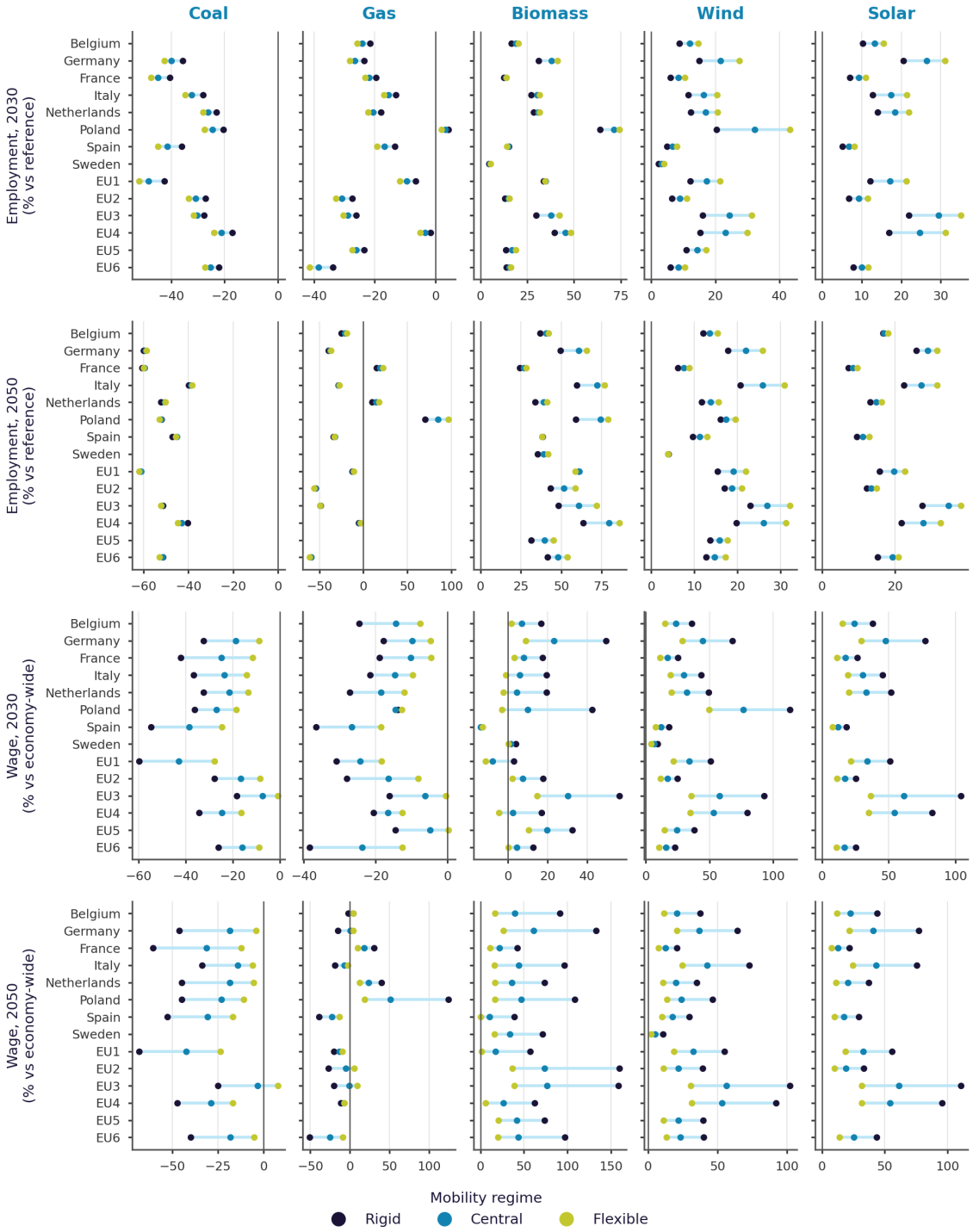

Figure 4.1. Skilled employment and wages by power-plant technology in the fourteen EU regions under the rigid, central and flexible mobility regimes, policy scenario, 2030 and 2050.
Employment in percent relative to the reference path of the same year; wages in percent relative to the economy-wide wage of skilled labour. A region is omitted for a technology that employs fewer than two skilled efficiency units. Source: O'Connell et al. (2026), own calculations.

The mobility regime has little effect on the energy transition itself. Coal- and gas-fired generation fall by nearly the same percentage under the three regimes in every region. Net of a small difference between the two scenarios in the base year, GDP in 2050 is 0.3% below the reference path in Sweden and 0.3 to 0.4% below in Germany. The largest reduction is 1.2, 1.1 and 1.1% in the composite region EU3[11] under the rigid, central and flexible regimes. The regime thus changes GDP by at most about 0.1 percentage point in any region.

In GEMINI-E3 EU, the regime does affect the timing of employment adjustment. In 2030, skilled employment in German coal plants is 36, 40 and 43% below the reference path under the three regimes. By 2050 the regimes have all converged to 59 to 60% below reference. Summed over all power-plant technologies, skilled employment in 2050 exceeds its reference level by 1, 3 and 4% in EU4 and by 16, 21 and 25% in Germany under the rigid, central and flexible regimes, respectively. Greater mobility thus raises the size of the generation workforce as well as the speed of its adjustment.

In GEMINI-E3 EU and under the current calibration, wages respond more strongly than employment. In Germany, the coal-plant wage is 32, 19 and 9% below the economy-wide wage in 2030 under the rigid, central and flexible regimes. In 2050 these gaps are 46, 19 and 4%, respectively. On the expanding side, the wind wage premium in 2030 ranges from 9, 6 and 4% in Sweden to 114, 77 and 50% in Poland. Across regions and technologies, the wage gaps under the rigid regime are one and a half to two and a half times those under the central regime. Gaps under the flexible regime are about half those under the central regime. Outside the energy sectors, employment in every other sector in 2050 is within 2% of its reference level and wages are within 3% of the economy-wide wage, as we would expect.

The directed search module translates these paths into labour market outcomes for Germany. In the contracting brown sector, the unemployment rate of skilled workers rises from 3.0% in 2023 to 4.1, 3.5 and 3.2% in 2030 under the three regimes. In the expanding green sector, the expected duration of a skilled vacancy rises from 1.23 quarters in 2023 to 1.77, 1.59 and 1.46 quarters in 2030. Higher mobility thus produces shorter unemployment spells for displaced fossil workers and shorter vacancy durations in renewables.

[11] EU1 to EU6 are composite regions of GEMINI-E3 EU that group the member states not modelled individually: EU1 (Croatia, Cyprus, Greece, Malta, Portugal), EU2 (Austria, Luxembourg), EU3 (Czechia, Hungary, Slovak Republic), EU4 (Bulgaria, Romania, Slovenia), EU5 (Estonia, Latvia, Lithuania) and EU6 (Denmark, Finland, Ireland). See DIAMOND Deliverable D3.6

4.3.1.2 Policy results

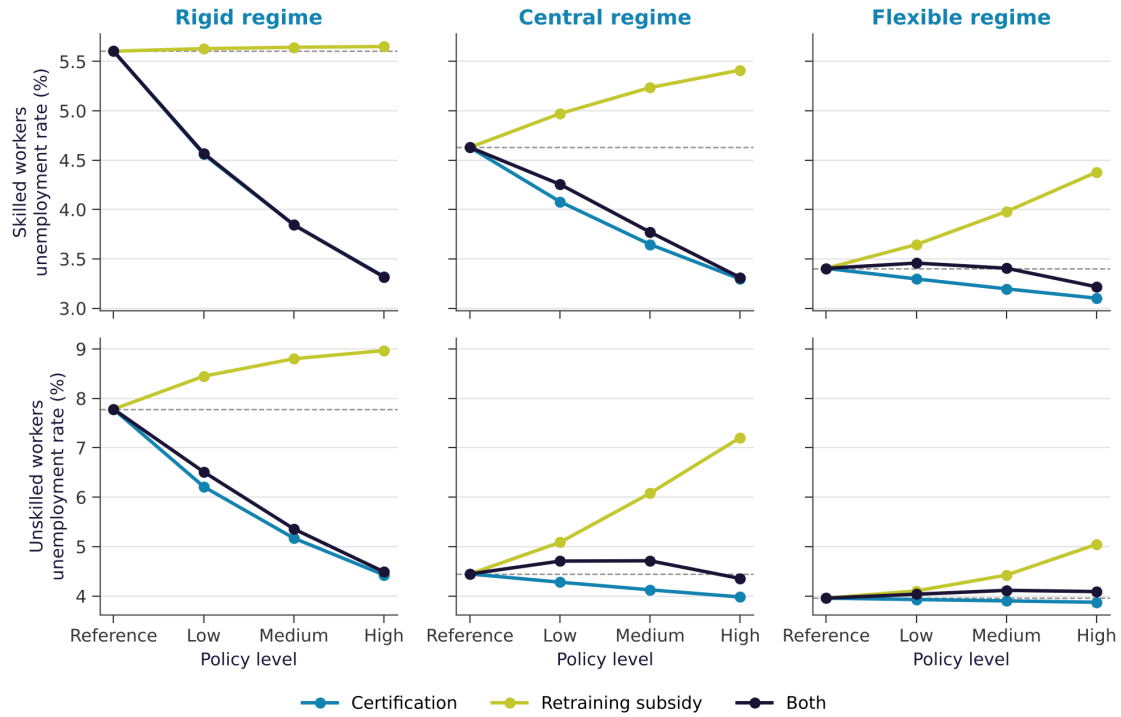

Figure 4.2. Unemployment rate of brown-origin workers in Germany in 2040 under skills certification, a retraining subsidy and both, at three policy levels, by mobility regime and skill type, policy scenario.
In the rigid regime, the lines for certification and for both policies coincide for skilled workers (within 0.01 percentage points), as the retraining subsidy has no effect on them. Source: O'Connell et al. (2026), own calculations.

Skills certification lowers the unemployment of brown-origin workers at every level, in every regime and for both skill types. Under the rigid regime in 2040, skilled unemployment falls from 5.6% to 4.6, 3.8 and 3.3% at the low, medium and high levels of certification. Unskilled unemployment falls from 7.8% to 6.2, 5.2 and 4.4%. The effect is smaller under the flexible regime, where fewer displaced workers search in the green sector. There, skilled unemployment in 2040 falls from 3.4% to 3.3, 3.2 and 3.1%.

The retraining subsidy alone does not reduce unemployment of brown-origin workers in any regime. Under the rigid regime it has practically no effect in 2030 and 2050, when all displaced workers already search in the green sector. In 2040 and 2045 it moves the remaining unskilled workers across and raises their unemployment, in 2040 from 7.8% to 8.4, 8.8 and 9.0%, while skilled unemployment is unchanged to within 0.1 percentage points. Under the flexible regime it raises the share of skilled brown-origin workers searching in the green sector in 2040 from 23% to 36, 51 and 66%. Their unemployment rate rises from 3.4% to 3.6, 4.0 and 4.4%. More workers apply for green jobs, but the probability that an application succeeds is unchanged, so retraining without additional policy only increases the queue.

Under the central regime, certification lowers skilled unemployment in 2040 from 4.6% to 4.1, 3.6 and 3.3% and unskilled unemployment from 4.4% to 4.3, 4.1 and 4.0%. The retraining subsidy raises the share of brown-origin workers searching in the green sector from 70% to 81, 89 and 94% (skilled) and from 23% to 42, 64 and 81% (unskilled), and their unemployment from 4.6% to 5.0, 5.2 and 5.4% and from 4.4% to 5.1, 6.1 and 7.2%. Combined with certification, unemployment stays within 0.6 percentage points of certification alone.

Combining the two policies under the flexible regime gives the search behaviour of the retraining run at an unemployment rate slightly above that of the reference run. In 2050 at the high level, 54% of unskilled brown-origin workers search in the green sector, with an unemployment rate of 4.2%. Under certification alone, 8% search

in the green sector at an unemployment rate of 3.9%. In the reference run, 8% do so at an unemployment rate of 4.0%. Certification offsets most, but not all, of the increase in unemployment that the subsidy causes on its own.

These results are specific to Germany. The module parameters are calibrated to German evidence where available, and brown and green are defined by technologies that contract or expand in Germany. But they illustrate how the module works in general and how the effect of each instrument will depend on the mobility regime. For the underlying working paper, we expect the direction of the effects to carry over to other regions, but not their size. The benefit of certification will be largest where the brown wage falls furthest, as in EU1, and smallest where brown labour markets hold up, as in Italy or EU3 under the flexible regime. The retraining subsidy, in contrast, has little to act on where brown wages collapse and does more harm where they do not (O'Connell et al., 2026).

4.3.2 Finance

4.3.2.1 Reference results and financing conditions

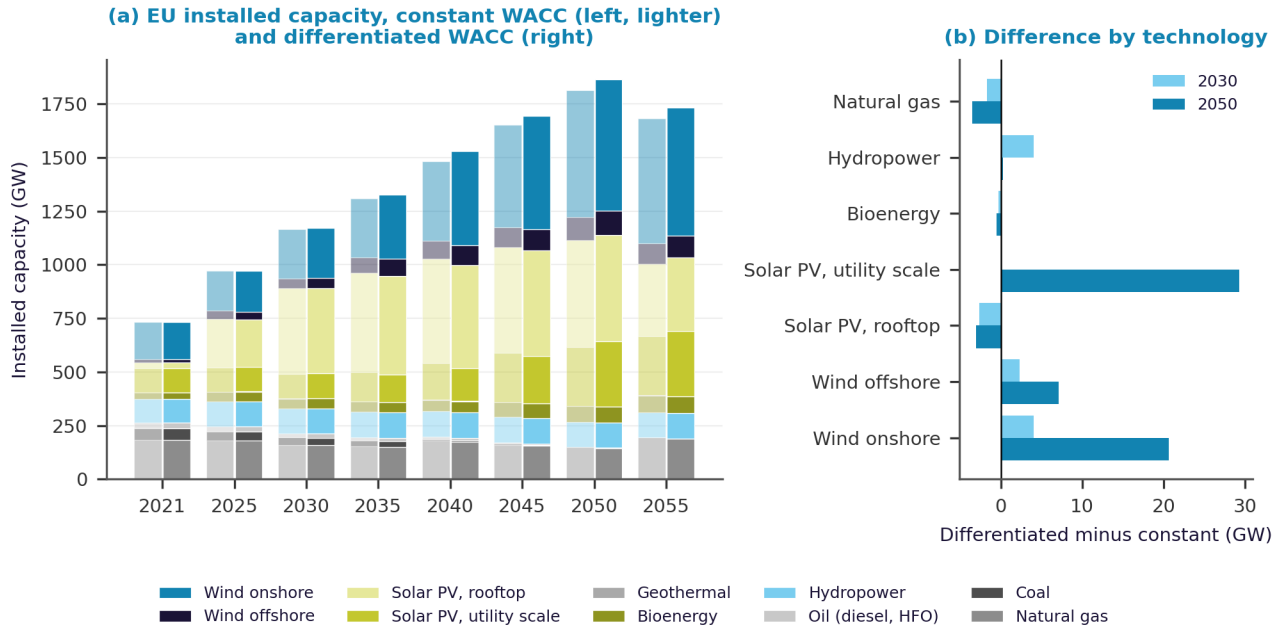

Figure 4.3. EU installed power capacity by technology (excluding nuclear) in CLEWs-EU with a constant WACC of 7.5% and with differentiated empirical WACCs
Without net-zero constraint, 2021 to 2055 (a), and the difference between the two runs in 2030 and 2050 (b). Source: Serebriakova et al. (2026), own calculations.

In CLEWs-EU, replacing the uniform discount rate with differentiated empirical WACCs raises total installed capacity in the EU in 2050 by 2.8%, excluding nuclear power (91 GW in 2021), which CLEWs-EU also models (Figure 4.3, left panel). Utility-scale solar PV shows the largest increase, at 10.6% by 2050, while rooftop solar PV is nearly unchanged. Wind capacity increases most in Belgium, Bulgaria, Estonia, Finland, Ireland, and Lithuania. Solar PV capacity increases mainly in Germany and Belgium. Most countries do not change their solar PV installation, among them Austria, Denmark, Spain, France, Italy and the Netherlands. Installed bioenergy and hydropower capacity is nearly unchanged (191.5 GW against 191.2 GW).

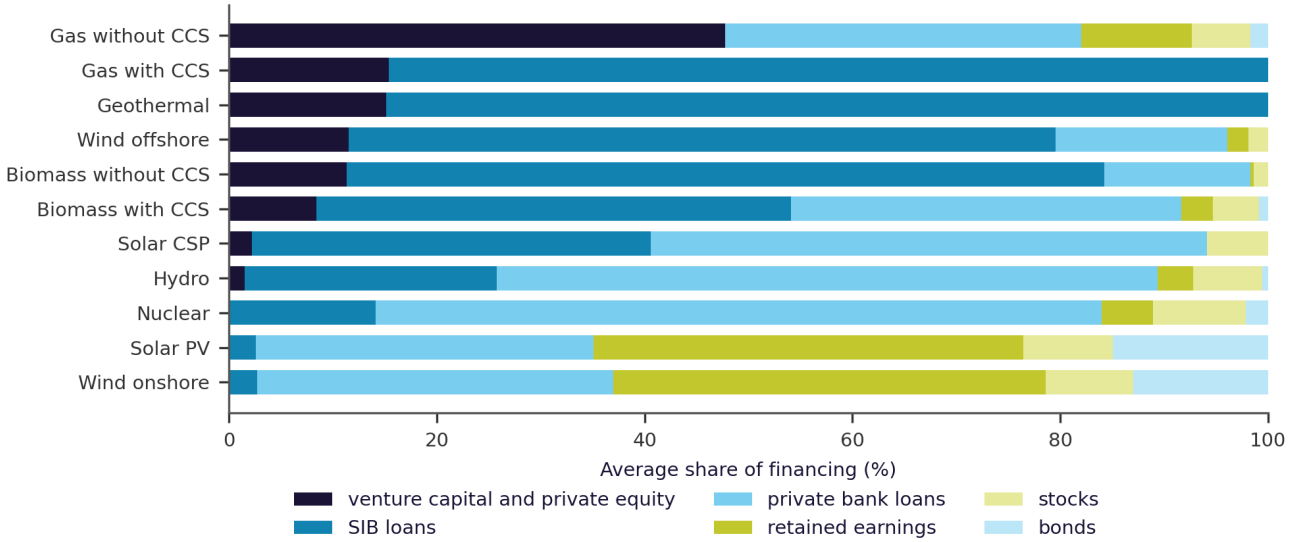

Figure 4.4. Average financing mix by technology, NEMESIS net-zero scenario, mean over countries and years. Coal and oil are not shown, as investment in these technologies is financed on the balance sheet of incumbent firms. Source: Serebriakova et al. (2026), own calculations.

In the NEMESIS net-zero scenario, the module assigns the lowest financing costs to solar and wind. Their WACCs go as low as 5%, with an average of about 9% over the countries and years with new investment. Fossil technologies end up being assigned very high WACCs. These are, however, best interpreted as a shadow price consistent with them being phased out. In our module, declining market shares translate into higher risk and more expensive funding sources, and the module does not yet distinguish between mature fossil technologies being phased out and immature renewable ones being phased in. Figure 4.4 shows that mature renewables, those with the highest normalised maturity scores (in 2050 about 63 for solar PV and 56 for onshore wind, against less than 30 for all other technologies), rely mainly on retained earnings, private bank loans and bonds. Technologies of intermediate maturity, such as solar CSP and biomass, rely mainly on SIB and private bank debt. When a technology seeks to finance new capacity, it meets a funding constraint in about 35% of the country-period-technology combinations with new investment. Constrained technologies include biomass with and without CCS, gas with CCS, offshore wind and geothermal, as well as coal and oil.

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4.3.2.2 Policy results

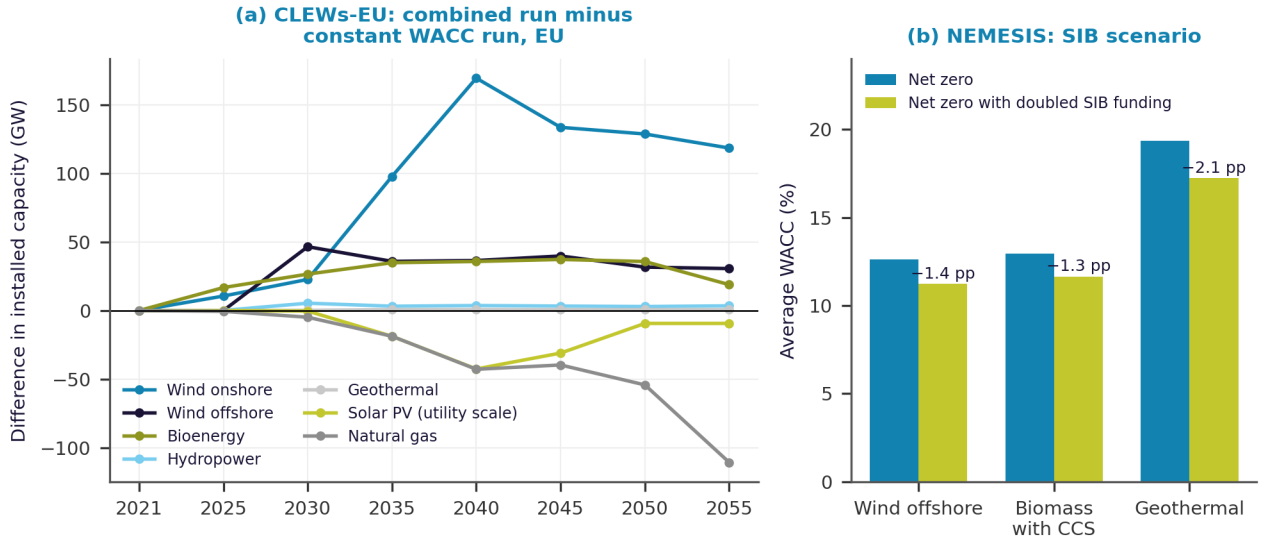

Figure 4.5. Effects of finance policies.
(a) Difference in EU installed capacity between the CLEWs-EU run with differentiated WACCs, net zero and green preferential interest rates and the constant WACC run under No (further) Action. (b) Average WACC in the NEMESIS net-zero scenario without and with doubled SIB funding. Source: Serebriakova et al. (2026), own calculations.

The green preferential interest rate results in CLEWs-EU (Figure 4.5, left panel) compare the constant WACC run under No (further) Action with a run that combines differentiated WACCs, a net-zero commitment and green rates. The differences in the figure therefore reflect the three changes together. With net zero, green rates alone would add 16.4 GW of capacity by 2050 (onshore wind +43.8 GW, offshore wind +5.2 GW, utility-scale solar PV -39.0 GW, rooftop solar PV -5.1 GW). In 2050, the combined run has 128.6 GW more onshore wind and 31.6 GW more offshore wind than the comparison run, while natural gas capacity is 54.2 GW lower and utility-scale solar PV capacity is 9.4 GW lower (the latter having still more than doubled compared to 2021). Rooftop solar PV capacity (not shown) is 47.7 GW lower. By 2055, natural gas capacity is 110.6 GW lower. We attribute the larger responses of wind to its higher capital intensity relative to solar PV.

Doubling SIB funding in NEMESIS (Figure 4.5, right panel) roughly halves the number of funding-constrained country-period-technology combinations for biomass with and without CCS and for offshore wind. For geothermal it reduces them by 90%. Consequently, the WACC falls by 1.4 percentage points for offshore wind, by 1.3 percentage points for biomass with CCS and by 2.1 percentage points for geothermal. Fossil technologies, including gas with CCS, are excluded from SIB loans under the green mandate and become more constrained. For gas with CCS, the number of funding-constrained combinations rises from 101 to 132 and its average WACC from 20% to 35%. For coal, gas and oil without CCS (not shown), the increase is small.

Green QE has almost no effect. Of the cases in which a technology meets a funding constraint, only 2% concern onshore wind and solar PV, all of them in Malta. A 50% increase in bond financing does not change these constraints. The average WACCs of solar PV and onshore wind fall by 0.02 percentage points on average, with almost no additional use of the bond market. The authors note that this agrees with DSGE studies that find small effects of green QE on the green energy sector (e.g. Ferrari & Nispi Landi, 2024). The NEMESIS results are outputs of the finance module given the NEMESIS installation paths. They do not yet include the effect of iterated WACCs on installation decisions in NEMESIS.

4.3.3 Consumer behaviour

4.3.3.1 Reference results and household heterogeneity

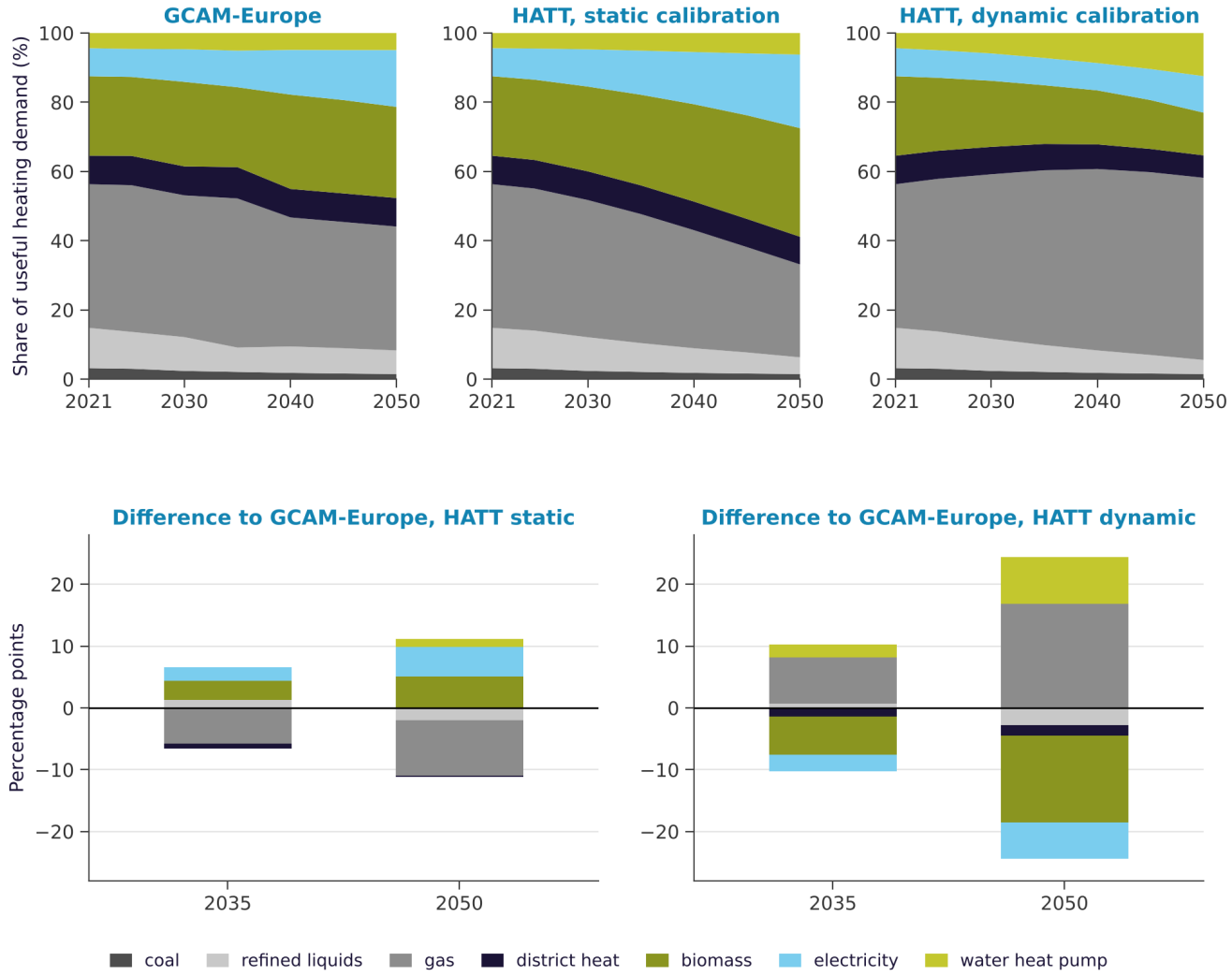

Figure 4.6. EU heating market shares (share of useful heating demand) by subsector in the no-policy baseline, 2021 to 2050 For GCAM-Europe with its native module and with HATT under static and dynamic calibration (top), and the difference between HATT and GCAM-Europe in 2035 and 2050 (bottom). Source: Morley et al. (2026), own calculations.

With static calibration, the HATT projections at the EU level are close to those of the native GCAM-Europe module (Figure 4.6, left and middle panels). Both show a gradual shift from gas and refined liquids towards electricity and biomass, which, in the absence of policy, is driven by changes in relative costs. In HATT the shift is somewhat stronger. By 2050, the combined market share of electricity and biomass is 9.9 percentage points higher than in GCAM-Europe. The combined share of gas and refined liquids is 11.0 percentage points lower. We attribute part of this difference to the S-shaped diffusion paths that HATT generates, which are more consistent with the innovation diffusion literature. The other part comes from the high and rapidly declining levelised costs of electric resistance heating, air-to-air heat pumps and biomass in the input data, combined with the additive nature of the calibrated parameter in HATT as opposed to the calibrated parameter in GCAM-Europe, which is multiplicative with price.

Dynamic calibration (Figure 4.6, right panel) gives a different projection, capturing recent trends in the historical data. The market share of gas grows from 41.5% in 2021 to about 53% in the 2040s and then levels off, biomass

declines from 23.0% to 12.3%, and the share of water heat pumps almost triples, from 4.4% in 2021 to 12.4% in 2050.

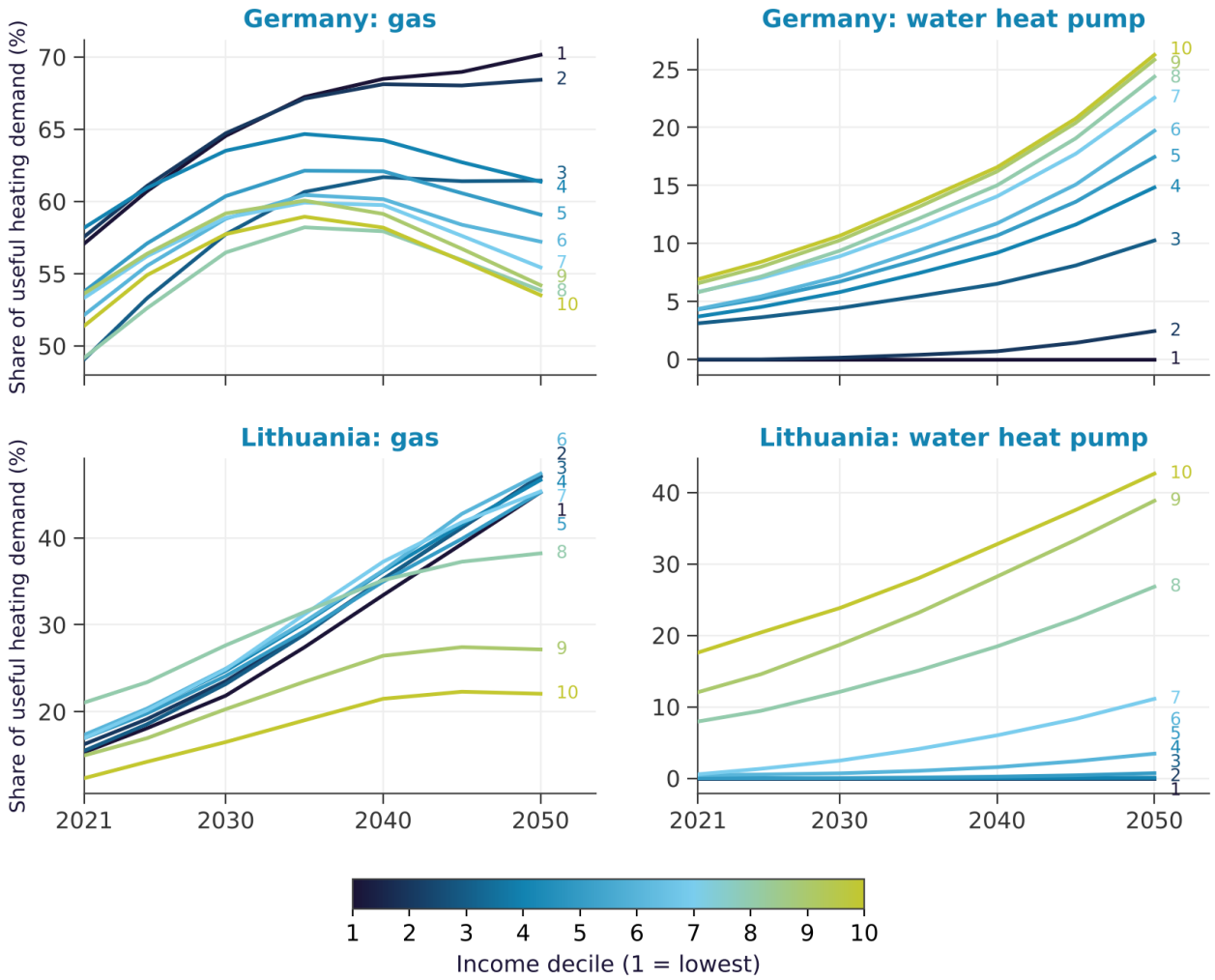

Figure 4.7. Market shares of gas and water heat pumps by income decile in Germany and Lithuania HATT under dynamic calibration, no-policy baseline. Source: Morley et al. (2026), own calculations.

In principle, adoption in HATT differs by income. In a no-policy scenario, this is clearly visible in a few countries under the dynamic calibration (Figure 4.7). In Germany, the market share of gas rises in every decile, from 49 to 58% in 2021 to between 54% in the top decile and 70% in the lowest decile in 2050. In the upper deciles, the gas share peaks around 2035 and then declines. At the start of the simulation the two lowest deciles cannot afford water heat pumps. The second decile gains access by 2030, due to rising income, but the first decile never gains access and most heat pump adoption takes place in the top half of the income distribution. In Lithuania, heat pump gains are concentrated in the top three deciles. Gas shares in the ninth and tenth deciles level off at 22 to 27% by 2050. In the bottom seven deciles, gas market shares continue to rise, from 15 to 17% in 2021 to 45 to 47% in 2050. Gas use thus becomes more concentrated among lower-income households. Under static calibration, no country combines a large increase in heat pump shares, a binding affordability constraint, and a large fossil fuel share, conditions necessary for the visibility of this trend of increasing energy inequality. Denmark is the only country in the static calibration no-policy scenario with a large absolute increase in heat pump shares, and it has a relatively small fossil fuel share.

4.3.3.2 Policy results

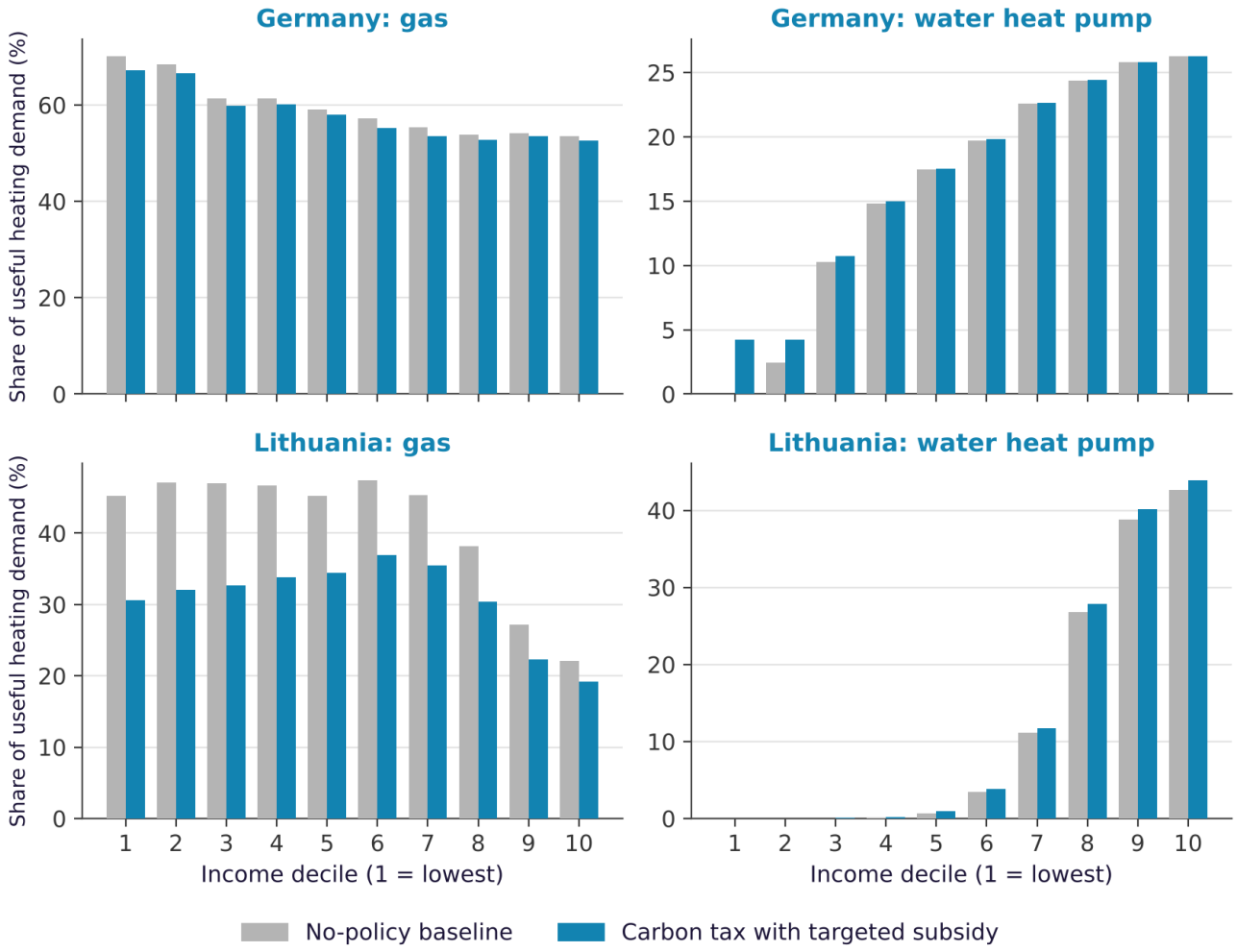

Figure 4.8. Market shares of gas and water heat pumps by income decile in Germany and Lithuania in 2050
No-policy baseline and carbon tax with targeted subsidy, HATT under dynamic calibration. Source: Morley et al. (2026), own calculations.

Combining the carbon tax with the targeted subsidy raises the EU market share of water heat pumps in 2050 only slightly, from 12.4% in the baseline to 13.7%. At EU level, the main effect of the policy is a shift from gas to biomass. The gas share falls from 52.6% to 42.0%, and the biomass share rises from 12.3% to 25.3%. In the bottom five deciles, which receive the higher subsidy rate of 50%, the heat pump share rises from 7.4% to 9.1%, and in the top five deciles from 16.3% to 17.3%. The gap in heat pump adoption between the top and bottom halves of the income distribution thus narrows by 0.7 percentage points. In Germany, the subsidy gives the two lowest deciles access to water heat pumps from 2025 onwards, and the heat pump share of the lowest decile in 2050 rises from zero to 4.2% (Figure 4.8). Gas shares fall by only 1 to 3 percentage points in each decile and remain highest, at about 67%, in the two lowest deciles. In Lithuania, the subsidy makes water heat pumps affordable for the second to fifth deciles from 2025, but the heat pump share of the bottom five deciles stays below 1%. The bottom seven deciles do move away from gas, whose share falls from 46.3% to 34.1%, but towards biomass, whose share rises from 22.1% to 37.9%. The model is built so that a carbon tax changes the lifetime cost comparison but not the affordability assessment of liquidity-constrained households, while an investment subsidy lowers the up-front cost that enters that assessment. The Lithuanian results show that removing the affordability constraint does not by itself lead to adoption.

As a sensitivity test, we also ran the scenarios under static calibration. The policy then has a larger effect on heat pumps. The EU share in 2050 rises from 6.2% to 12.4%, and that of the bottom five deciles from 3.4% to 8.8%. Because the top five deciles gain even more, from 8.4% to 15.1%, the adoption gap between the two halves widens by 1.4 percentage points. The size of the policy effect, and the direction of its distributional effect, thus depend on how the module is calibrated. The two calibrations can differ strongly for individual countries. Static calibration takes current market shares to reflect preferences, so shares change only when relative costs change; as gas prices rise relative to other fuels, gas declines. Dynamic calibration also carries forward recent trends. In Lithuania, where the gas share had been rising, rising gas prices are not enough to reverse that trend: by 2050 the gas share of the bottom seven deciles is about 46% under dynamic calibration and about 6% under static calibration, from 15 to 17% in 2021.

4.4 Discussion

The three strands share one result in the reference runs. Representing a friction explicitly changes the distribution and timing of adjustment more than the aggregate outcomes. In the labour strand, the mobility regime changes wages and unemployment by sector but has a small effect on generation, emissions and GDP. In the consumer strand, heterogeneous adoption leads to a concentration of gas heating among lower-income households in Germany and Lithuania under dynamic calibration. In the finance strand, differentiated WACCs raise total EU installed capacity in CLEWs-EU by 2.8% by 2050, and utility-scale solar PV by 10.6%, while most countries do not change their solar PV installation. It is the distribution of outcomes over heterogeneous agents that changes, even if the aggregate outcomes do so much less. However, as the transition runs into political opposition and a "fair transition" is deemed essential to maintain momentum, these distributional impacts are exactly what policy should consider.

The policy results that are available point in one direction. Instruments that act on the binding friction have larger effects than instruments that act on a margin that does not bind. Skills certification raises the success rate of switching and lowers unemployment. The retraining subsidy raises the number of attempts to switch and, on its own, does not lower unemployment. Additional SIB funding relaxes funding constraints for less mature technologies. Green QE adds bond financing for mature technologies that are rarely constrained, and has almost no effect. In the consumer strand, the subsidy targeted at low-income households reaches the deciles whose heat pump adoption the carbon tax alone cannot change, because the subsidy acts on the affordability constraint. Under dynamic calibration the effect on adoption is modest, however, and the adoption gap between income groups narrows only slightly. These findings are in line with the policy literature reviewed in Sanders et al. (2026). There, studies that model heterogeneity find that targeted instruments can address constraints that price-based instruments leave untreated.

Our results, however, still have several limitations. All three modules are soft-linked. Only HATT is iterated with its host model to a consistent solution, so far for the no-policy baseline only, and the finance module and NEMESIS have so far completed only a first feedback round, without iterating to a consistent solution. The labour policy results are for Germany only and serve as a first illustration, whereas the policy intensities are also illustrations and are yet to be calibrated on actual policy proposals. Several behavioural parameters in all three modules are assumed or follow a preliminary calibration. Examples are the 25% affordability threshold in HATT and the search costs and conversion probabilities in the labour module. Each module also covers only one market. Interactions between markets, such as the effect of credit constraints on household technology adoption, or of labour market outcomes on household incomes are not represented. DIAMOND Deliverable D4.5 notes that the results should therefore inform further calibration and empirical work before policy conclusions are drawn. The same holds for the results reported here.

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4.5 Conclusions

On the first research question (i.e., How do labour market frictions, financing conditions and heterogeneous consumer behaviour change projected transition pathways and their distributional outcomes?), the results show that labour market frictions, financing conditions and heterogeneous household behaviour change the distribution and timing of the transition. Their effect on aggregate outcomes is non-trivial, but smaller in the cases simulated so far. On the second research question (i.e., Which policy instruments act on these frictions?), the available results show that instruments targeted at a binding friction are more effective than instruments acting on a margin that does not bind. This holds for skills certification relative to a retraining subsidy and for SIB funding relative to green QE. For heat pumps, combining a carbon tax with a subsidy targeted at low-income households raises adoption in the deciles constrained by up-front costs, but the effect is modest and the adoption gap between income groups narrows only slightly.

Future research will extend the labour policy simulations to other EU regions. This requires adapting the module parameters and the definition of brown and green technologies to each region. It could also assess a scenario in which carbon price revenues are recycled into training and mobility support for displaced workers, as proposed in D4.5. Such a scenario would combine a price-based instrument with the targeted instruments studied here. For the finance strand, work is under way to iterate the finance module and NEMESIS, feeding the WACCs back into NEMESIS until financing conditions and installation pathways are mutually consistent. A first feedback round has been run and we expect converged results to be available shortly. For the consumer strand, work is underway to replicate and extend the HATT-GCAM-Europe protocol to OPEN-PROM as well. OPEN-PROM has one representative household per country and does not distinguish residential energy demand by its end-use application, so the link requires additional data on the income distribution and on heating demand by income, as well as work on disaggregation of OPEN-PROM data on end-use energy demand in the residential sector. Future research will also report results for the four remaining consumer policy scenarios, which compare the carbon tax and the subsidies on their own. Updated results will be made available as they become available in the underlying working papers, which can be found here.

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5 The impact of societal preferences and trends on climate action

IAMs have been useful for assessing climate change pathways and designing policies to effectively mitigate carbon emissions, including measures targeting consumer behaviour (Keppo et al., 2021; Weyant, 2017). However, IAMs have limitations when it comes to modelling consumer behaviour that might affect scenario development and evaluation. These limitations have been prominently discussed by the research field itself (Keppo et al., 2021; Wilson et al., 2021), and they include the lack of representing heterogeneous actors as well as the inaccurate modelling of technology diffusion and dynamics. It has been argued that these limitations can skew modelling results and the resulting policy recommendations, for example, by providing overly optimistic or pessimistic technology diffusion estimates (McCollum et al., 2017; Wilson et al., 2021). Mainly focusing on financial drivers of decision-making (e.g., investment costs, operating costs) risks assuming actors to be rational (even though perceptions of financial outcomes are also biased and prone to heuristic decision-making; Kahneman, 2003; Tversky & Kahneman, 1974) and ignoring additional important drivers, such as social motivations, other personal motivations, and emotions or affective states (e.g., irrational focus on electric vehicle (EV) range because of range anxiety; Pettifor et al., 2017; Rezvani et al., 2015). In addition, the lack of actor heterogeneity limits modelling capabilities in various ways. First, it is impossible for IAMs that do not represent actor heterogeneity to give information about which societal groups adopt certain behaviours, like adopting a clean technology (McCollum et al., 2017; Rai & Henry, 2016). Second, these IAMs cannot capture which societal groups are most positively or negatively affected by implemented policies, such as carbon prices or technology subsidies (Borenstein & Davis, 2025; Stechemesser et al., 2024). Third, they can, therefore, also not implement group-specific policies well (e.g., income-sensitive subsidies).

These limitations of IAMs - lack of representing heterogeneous actors and inaccurate modelling of technology diffusion - have been addressed in the DIAMOND project within Deliverable D4.6 (DIAMOND Consortium, 2026), where a behavioural module was developed based on psychological theory. This module was subsequently soft-linked with three IAMs – CLEWs-EU, GCAM Europe, and OMNIA – to test the effect a more accurate modelling of consumer behaviour has on various system-level outcomes. In this deliverable, we build on Deliverable D4.6 by applying the previously developed behavioural module to various disruptive events (combinations of tariffs on EVs and uncertainty in gasoline and electricity prices).

We chose EV adoption as the target behaviour because i) it represents a technology whose diffusion is heterogeneous across individuals depending on their socio-economic status, psychological characteristics, and contextual embedding (Günther et al., 2025), and ii) the transport sector is highly relevant for climate change, accounting for around 20% of global CO2-equivalent emissions (CO2eq-emissions; Morfeldt et al., 2021; Ritchie, 2020), with around 40% of transport emissions coming from passenger cars or vans (IEA, 2025; IPCC, 2023). While effective solutions include the reduction of individualised mobility patterns and the expansion of the public transport sector, not every individual will be able to refrain from individualised mobility (IPCC, 2023). To decouple the private transport sector from CO2eq-emissions, one solution lies in the replacement of conventional, fossil fuel-powered cars with EVs (IEA, 2024). Given the importance of EV uptake for system-level emission reduction, accurate modelling of their diffusion is key to preventing unrealistic technology adoption pathways and biased policy recommendations (McCollum et al., 2017).

The purpose of this section is to describe how disruptive events affect consumer behaviour based on past research and a new study conducted in three countries (Section 5.1 “Disruptive events and individual behaviour”), outline the behavioural module and soft-link (Section 5.2 “Behavioural Module and Soft-Link”), and give insights into how the different versions of the module (without disruptive events and different disruptive event scenarios) affect

modelling outcomes (Section 5.3 "Soft-link results"). Finally, we discuss how modelling outputs compare between the different behavioural module versions and the DIAMOND baseline scenario without any soft-link (Section 5.4 "Discussion").

These analyses and discussions of how a more accurate representation of consumer heterogeneity and decision-making affect IAM output directly map onto the stakeholder-informed Research Questions (RQs) 1 and 3 within the topic of "People in Transition" (see Deliverable D5.2, Section 5.3.5 for the final questions and Deliverables D2.5/D2.7 for the transdisciplinary process through which the questions were derived). The RQs are "How does including household heterogeneity in IAMs influence forecasts for electric vehicle adoption (under different external events)?" (RQ1) and "How does including household decision-making based on psychological factors in IAMs influence forecasts for electric vehicle adoption?" (RQ3).

The data collection for the disruptive events further allowed setting up an agent-based model (ABM) to investigate the effect of disruptive events on cumulative technology adoption (ABM result described in Section 5.1). We use the ability of ABMs to present results disaggregated by income to address the stakeholder-informed RQs 2 and 4 within the topic of "People in Transition". These are "Which policies are effective in stimulating the transition to e-mobility while mitigating negative financial impact on low-income households?" (RQ2) and "Which policies enable households of different socio-economic groups to participate in the transition to e-mobility?" (RQ4). In Section 5.4, we compare the outcomes of the different system modelling approaches (ABM and IAMs) and then derive some recommendations for policymakers and system modellers (Section 5.5 "Conclusions").

5.1 Disruptive events and individual behaviour

5.1.1 Theoretical background

EV adoption is increasing globally, but it is doing so in an environment marked by growing geopolitical and economic disruption (Barragan-Contreras et al., 2025). While China has become a leading producing nation of EVs, several countries including the United States and the European Union have put tariffs on Chinese EVs to protect national car industries. In addition, tariffs imposed by the United States on imported vehicles and parts have raised costs across global auto supply chains (M. Liu et al., 2026). Recent geopolitical events including the full-scale invasion of Ukraine by Russia and the blockade of the Strait of Hormuz have severely shocked the energy system, leading to sharp increases in energy prices that change the cost of running EVs relative to internal combustion engine vehicles (ICEVs; IEA, 2026). These types of shocks may affect consumers differently, and some accelerate EV diffusion whereas others slow it down (Barragan-Contreras et al., 2025; IEA, 2026; M. Liu et al., 2026).

In their proposal for a framework for analysing disruption within energy transitions, Barragan-Contreras et al. (2025) discuss the multifaceted nature of disruption, including its links to and implications for just energy transitions, the global order, and the design of effective transition policy. They argue that disruption may have negative consequences for certain societal groups but can also accelerate energy transitions. Another key point of the framework is the diversity of possible sources of disruption, going beyond the classic idea within political economics of disruptive innovation (Kivimaa et al., 2021) to also include shifts away from fossil fuels and towards renewables, industrial policy (e.g., move towards protectionism in key states of the global North), and the "polycrisis" (Rakowski et al., 2025) that arose globally since 2020, including crises as the COVID-19 pandemic, global inflation, and the full-scale invasion of Ukraine by Russia.

Several recent studies have empirically investigated the impact of disruption on energy transitions. Based on an analysis of EV market data from G20 countries, Liu et al. (2026) conclude that import tariffs on EVs have led to stagnated development of the U.S. EV market. In another study focussing on the personal vehicle market, Yan et

al. (2022) found that purchase intentions of vehicles increased in China during the COVID-19 pandemic despite negative household income shocks, driven by the desire for a private, protected space during commutes. In an empirical study on the impact of disruption on the transition towards renewables, Ivanovski and Marinucci (2021) used panel data from 23 countries over nearly two decades to demonstrate that high levels of energy policy uncertainty and volatile energy prices, resulting from disruptive events such as financial crises and the COVID-19 pandemic, generally hamper the transition towards renewable energy. While the data reveals a negative correlation between energy policy uncertainty and renewable energy consumption, their time-varying analysis shows this relationship fluctuates, occasionally turning positive during periods of high climate awareness or energy demand. Furthermore, there is a significant literature base on the impact of disruptive events on shopping behaviour (Gigliotti & Rizzi, 2023). However, empirical studies on the impact of disruption of consumer purchases of durable goods, such as energy technologies, remain limited overall and have typically not been included in simulation-based scenarios of the diffusion of household energy technologies (Barragan-Contreras et al., 2025; Kivimaa et al., 2021).

Simulation models of the energy transition are well suited to study the impact of disruption on energy transitions because they support exploratory what-if analysis of various disruptive and non-disruptive scenarios (Ciola et al., 2023; Hoekstra et al., 2017; Turco et al., 2023). ABMs are particularly suited for capturing how consumer groups respond differently to disruptive events, because they are not based on equilibrium assumptions and can model different decision-making mechanisms in a heterogeneous agent population (Hoekstra et al., 2017; Konc et al., 2022; Rai & Henry, 2016). The decision rule determining heterogeneous agent behaviour in such models can be empirically grounded through discrete choice experiments (DCEs; Günther et al., 2026; Klein et al., 2020; Scorrano & Danielis, 2022; Van Der Kam, Lagomarsino, Azar, et al., 2024; Zhang et al., 2011). There is a large literature on DCEs for EV adoption that estimate preference heterogeneity through latent class models (Greene et al., 2018; Pettifor et al., 2017; Van Der Kam, Lagomarsino, Meuleman, et al., 2024), but this is developed almost entirely under "stable world" conditions, without asking how preferences change under drastically shifting circumstances.

Our approach addresses this gap by developing an ABM of EV diffusion, in which agent decision-making is empirically informed by a two-wave multi-country consumer choice study of EV adoption under disruptive and non-disruptive conditions. Specifically, we are interested in the effect of these disruptive events on EV adoption decision-making, whether this effect differs across socio-economic groups, and what role policy can play in buffering or amplifying these effects. We collected data across the U.S., Germany, and South Africa. We choose these three countries because they differ in key contextual factors such as tariff policies, sensitivity of the energy system to shocks, and political stability. This paper contributes to the energy transition and EV adoption literatures by proposing a novel approach to empirically estimate how EV adoption preferences shift under disruption at the individual level, and to translate these estimates into system-level simulations of how shocks and policy interventions jointly shape the pace and equity of EV adoption under volatile market conditions.

5.1.2 Method

We present an empirically grounded ABM to simulate the transition to electrified personal mobility; see Figure 5.1. Model input consists of various sources, including external technology and policy scenarios, and an original two-wave multi-country consumer study grounded in the risks-as-feelings framework (Loewenstein et al., 2001). Both waves contain a DCE on EV adoption, either without disruption (Wave 1) or with disruption (Wave 2). We use these to calibrate agent decisions, with parameters reflecting preferences identified through the DCEs. Then the model simulates EV diffusion as influenced by individual factors, including preferences, risks perceptions, and affect, in interaction with contextual developments, including technological characteristics, policy, social norms, and specific disruptive events, namely the introduction of tariffs and volatility in fuel and electricity prices. The

primary outputs are EV adoption trajectories over time and across socio-economic groups. The rest of this section discusses these components in detail.

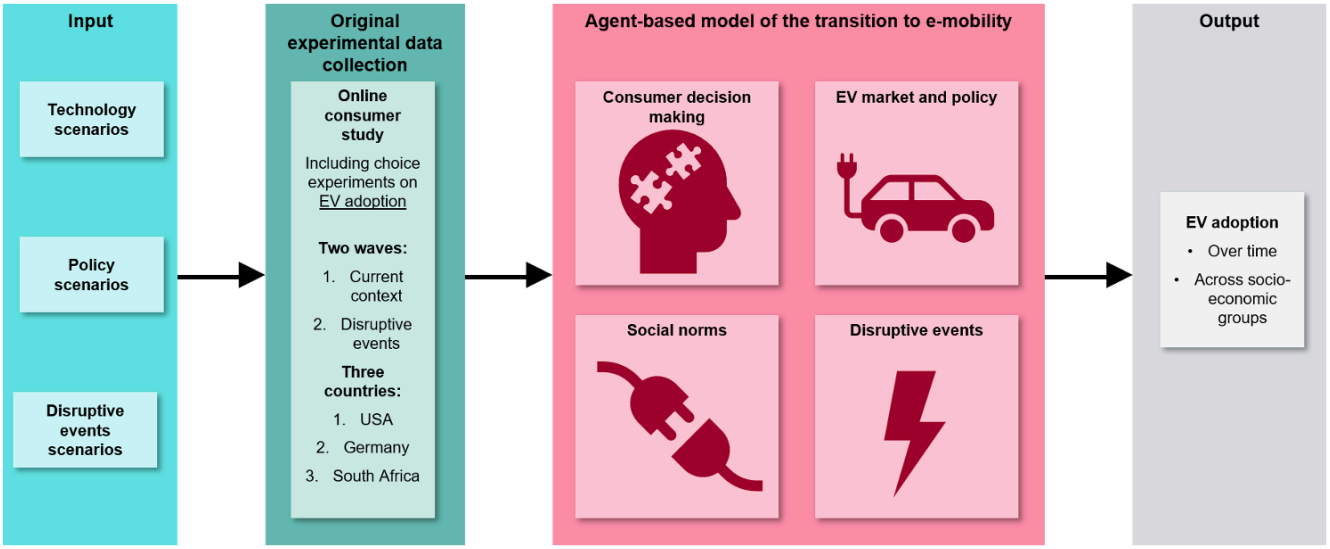

Figure 5.1. Behavioural Module overview

5.1.2.1 Input

Technology scenarios. The specific characteristics of the EVs that evolve in our simulation are purchase price and battery range. The development of EV purchase prices is based on empirical findings of learning rates for EVs (Weiss et al., 2019, Barwich et al., 2025), and the increase in EV range is based on extrapolation of historical increases (IEA, 2026). Section 5.1.2.4 presents implementation details.

Policy scenarios. Across our scenarios with and without disruption, we include two common financial policies to stimulate EV adoption among the agents. Firstly, we model a subsidy on the purchase price of EVs to make them more affordable. Secondly, we model a carbon tax on gasoline to increase the relative financial advantage of driving an EV versus an ICEV. The level of the subsidy and carbon tax is varied across the scenarios. As a more radical policy, we also include a ban on ICEV sales, which is not implemented suddenly but in 2030, and announced in 2025: the start of the simulation.

Disruptive events scenarios. For the purposes of this deliverable, we define disruptive events as exogenous, radical, and unanticipated changes to the consumer market for personal vehicles that have the potential to alter how consumers decide between EVs and ICEVs. Such events can arise from different kinds of mechanisms, including government policy, trade disputes, and downstream consequences of broader geopolitical or economic crises. Our definition incorporates key aspects of disruption as defined by previous literature, including the magnitude of change of markets (Kivimaa et al., 2021) and the various possible causes of disruption (Barragan-Contreras et al., 2025), while making it specific to the core topic of this study: the transition towards electrified personal mobility.

The disruptive events selected for this study are inspired by recent, real-world cases. The first event is tariffs on EVs, drawing on the tariffs imposed on Chinese EVs by several countries, including the U.S. and the European Union, as well as the broader use of tariffs as a policy tool under the second Trump administration. The second event is energy price uncertainty, reflecting the steep increases and fluctuations in both gasoline and electricity prices following Russia's full-scale invasion of Ukraine in 2022 and the 2026 war between the U.S. and Iran around the Strait of Hormuz. Grounding our disruptive events in these actual cases ensures that the scenarios modelled in our study are empirically relevant and reflect disruptions consumers are actually exposed to.

5.1.2.2 Decision framework

The adoption decision model is based on the risks-as-feelings framework (Loewenstein et al., 2001); see Figure 5.2 for an overview. This framework combines expected utility models with the principle that decisions under risk and uncertainty are shaped by both cognitive and affective mechanisms. In this model, cognitive processes are captured by two variables: individual importance (Importance) and perceived probability of decision outcomes (Subjective probabilities). These variables account for individual differences in how people prioritise and evaluate various outcomes during decision-making. The Importance variables represent the importance of achieving specific goals by adopting an EV to the individual decision-maker, operationalised as the relative weight individuals place on the factors of investment costs, potential savings, vehicle range, and the announcement of an ICE vehicle sales ban. The selection of these attributes draws on prior research into barriers and determinants of low-carbon technology adoption (Singh et al., 2020). The Subjective probabilities variables reflect individual expectations regarding the likelihood of realising specific outcomes when adopting an EV, such as cost savings from EV adoption. Affective processes in the model include affect towards EVs and ICEs. These include both positive affect and negative affect, which are based on the intensity of specific emotions related to these issues (Brosch, 2021). Additionally, our framework accounts for the influence of peer behaviour on decision-making, i.e., the impact of the number of other households adopting EVs on EV adoption (Wolske et al., 2020). Specifically, we include the effect of the number of other households within the same income group on EV adoption.

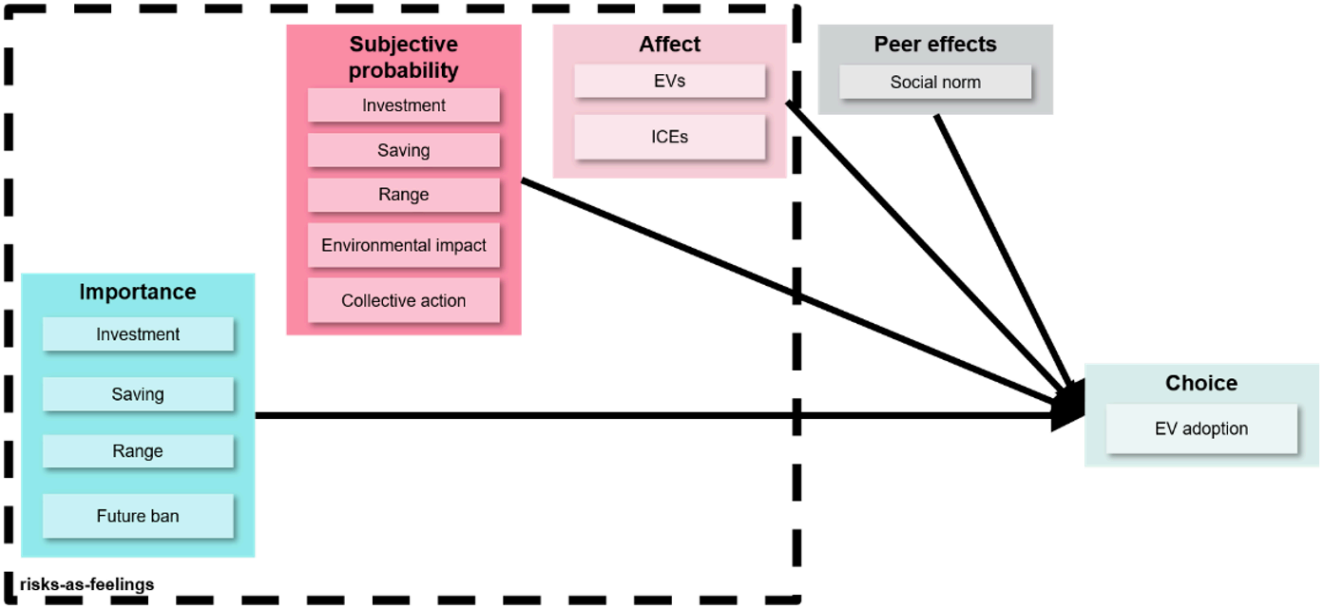

Figure 5.2. Adoption decision model, adapted from the risks-as-feelings framework (Loewenstein et al., 2001)

5.1.2.3 Original experimental data collection

We administered two DCEs across the two waves to assess preferences for EV adoption under contexts with and without disruption. Participants were representative in terms of gender, age, and education level, from the U.S. (N = 601, recruited via Prolific between September and December 2025), Germany (N = 671, recruited via Prolific (n = 401) and Consumerfieldwork GmbH (n = 261) between September and December 2025), and South Africa (N = 599, recruited via Prolific between September 2025 and January 2026). Participants who either owned a car or indicated they are planning to buy a car in the future (n = 594 for the U.S., n = 614 for Germany, and n = 598 for South Africa) were invited for the second wave between three days and two weeks after completing the first wave. The number of completions of Wave 2 are n = 537 for the U.S., n = 508 for Germany, and n = 485 for South Africa.

We designed separate DCEs targeting different vehicle size categories: small (A-segment and B-segment), medium (C-segment), and large (D-segment or larger); attribute and level details are provided in Table 5.1. Respondents first selected the vehicle size category they would consider for future purchases and then completed only the DCE corresponding to their chosen category. While the attributes remained consistent across the different DCEs, some attribute levels varied between them. In each DCE, respondents completed 18 trials presenting one hypothetical EV offer per trial, indicating whether they would purchase the vehicle when replacing their current one. The selection of choice tasks for the experiment followed a Bayesian D-efficient fractional factorial design, comprising two blocks of 18 unique passenger car sets for each of the three size categories, implemented using the R package *idefix* (Traets et al., 2020).

The experiment systematically varied several key attributes representing important factors in EV adoption decisions. These include purchase price after subsidies, electricity and gasoline costs of driving the EV and a comparable ICEV, and EV range. Additionally, we examined the influence of social norms by incorporating the number of EV adopters among peers within the same income group as an attribute. Finally, we added an attribute indicating whether a future ICEV sales ban had been announced, as this may affect current purchase decisions even before implementation.

Table 5.1. Attributes and attribute levels of the EV adoption DCEs used in Wave 1 (no disruption).
Note that the attribute and attribute levels for Range, Number of EV adopters among your income group, and ICE vehicle sales ban are the same across the two waves

Attribute	**Vehicle size**	***Levels***		
		U.S.	**Germany**	**South Africa**
Price (after subsidy)	Small	7.5; 11; 14.5 (k $)	7.5; 11; 14.5 (k €)	94.5; 133; 171.5 (k R)
	Medium	19; 34; 49 (k $)	19; 34; 49 (k €)	150; 205; 260 (k R)
	Large	55; 70; 85 (k $)	55; 70; 85 (k €)	358.5; 468; 577 (k R)
Electricity costs for driving	Small	3; 5; 7 ($ / 100 mi)	3; 5; 7 (€ / 100 km)	44; 66; 88 (R / 100 km)
	Medium	4; 6; 8 ($ / 100 mi)	4; 6; 8 (€ / 100 km)	55; 82; 109 (R / 100 km)
	Large	4; 7; 10 ($ / 100 mi)	5; 7; 9 (€ / 100 km)	62; 93; 124 (R / 100 km)
Gasoline costs for comparable car	Small	6; 13; 19 ($ / 100 mi)	7; 14; 20 (€ / 100 km)	100; 201; 302 (R / 100 km)
	Medium	8; 17; 25 ($ / 100 mi)	8; 16; 25	130; 245; 360 (R / 100 km)
	Large	12; 23; 33 ($ / 100 mi)	13; 24; 34 (€ / 100 km)	212; 336; 520 (R / 100 km)
Range	Small	150; 260; 370 (mi)	240; 420; 600 (km)	240; 420; 600 (km)
	Medium	190; 300; 410 (mi)	300; 480; 660 (km)	300; 480; 660 (km)
	Large	230; 340; 450 (mi)	370; 550; 730 (km)	370; 550; 730 (km)
Number of EV adopters among your income group		5; 40; 75 (%)	5; 40; 75 (%)	5; 40; 75 (%)
ICE vehicle sales ban		No ban; In 1 year; In 5 years;	No ban; In 1 year; In 5 years;	No ban; In 1 year; In 5 years;

The DCE of wave two had the same underlying structure, but with several adaptations to reflect our disruptive scenarios. First, the following text, shown before the start of the experiment, introduced the new experiment to recurring respondents:

> *"Imagine that **a political crisis** has hit your country. Due to geopolitical tensions, tariffs have been implemented on electric vehicles and energy imports. This has led to supply chain disruptions and instable global energy markets. These factors have also contributed to increased costs for electric vehicles as well as gasoline and electricity prices. The extent of price increases varies, reflecting potential market responses to supply shortages, shifts in global demand, and government policies to*

counter high prices for consumers."

Table 5.2 presents the attributes and their levels for the experiment of Wave 2. The attribute *Price (after subsidy)* was changed to *Price (after subsidy and tariff)* and included one higher price level to reflect increased purchase prices through tariffs. Furthermore, the attributes *Electricity costs for driving* and *Gasoline costs for comparable car* now vary in terms of the maximum upward fluctuations of expected price levels rather than fixed price points. As reference value for the price fluctuations, the middle attribute levels from Wave 1 are used. The maximum of the fluctuation is up to 100% higher than this reference value which, could lead to higher prices than in Wave 1.

Table 5.2. Attributes and attribute levels of the EV adoption choice experiments used in Wave 2 (disruption).
Note that the attribute and attribute levels for Range, Number of EV adopters among your income group, and ICE vehicle sales ban are the same across the two waves

Attribute	Vehicle size	*Levels*		
		U.S.	**Germany**	**South Africa**
Price (after subsidy and tariff)	Small	7.5; 11; 14.5; 18 (k $)	7.5; 11; 14.5; 18 (k €)	94.5; 133; 171.5; 210 (k R)
	Medium	19; 34; 49; 64 (k $)	19; 34; 49; 64 (k €)	150; 205; 260; 315 (k R)
	Large	55; 70; 85; 100 (k $)	55; 70; 85; 100 (k €)	358.5; 468; 577; 686 (k R)
Electricity costs for driving	Small	5; Varies between 5 and 7; Varies between 5 and 10 ($ / 100 mi)	5; Varies between 5 and 7; Varies between 5 and 10 (€ / 100 km)	66; Varies between 66 and 88; Varies between 66 and 132 (R / 100 km)
	Medium	6; Varies between 6 and 8; Varies between 6 and 12 ($ / 100 mi)	6; Varies between 6 and 8; Varies between 6 and 12 (€ / 100 km)	82; Varies between 82 and 109; Varies between 82 and 164 (R / 100 km)
	Large	7; Varies between 7 and 10; Varies between 7 and 14 ($ / 100 mi)	7; Varies between 7 and 9; Varies between 7 and 14 (€ / 100 km)	93; Varies between 93 and 124; Varies between 93 and 186 (R / 100 km)
Gasoline costs for comparable car	Small	13; Varies between 13 and 19; Varies between 13 and 26 ($ / 100 mi)	14; Varies between 14 and 20; Varies between 14 and 28 (€ / 100 km)	201; Varies between 201 and 302; Varies between 201 and 402(R / 100 km)
	Medium	17; Varies between 17 and 25; Varies between 17 and 34 ($ / 100 mi)	16; Varies between 16 and 25; Varies between 16 and 32 (€ / 100 km)	245; Varies between 245 and 360; Varies between 245 and 490 (R / 100 km)
	Large	23; Varies between 23 and 33; Varies between 23 and 46 ($ / 100 mi)	24; Varies between 24 and 34; Varies between 24 and 48 (€ / 100 km)	336; Varies between 336 and 520; Varies between 336 and 672 (R / 100 km)
Range	Small	150; 260; 370 (mi)	240; 420; 600 (km)	240; 420; 600 (km)
	Medium	190; 300; 410 (mi)	300; 480; 660 (km)	300; 480; 660 (km)
	Large	230; 340; 450 (mi)	370; 550; 730 (km)	370; 550; 730 (km)
Number of EV adopters among your income group		5; 40; 75 (%)	5; 40; 75 (%)	5; 40; 75 (%)
ICE vehicle sales ban		No ban; In 1 year; In 5 years;	No ban; In 1 year; In 5 years;	No ban; In 1 year; In 5 years;

5.1.2.4 Diffusion model

Our agent-based diffusion model simulates EV adoption decisions of consumer agents over time, who evaluate whether to adopt an EV within a context that incorporates the price and range of EVs, the costs of driving an EV relative to an ICEV, the implemented policy mix, social norms regarding EV adoption, and the influence of disruptive events. Agents have a specific duration they use a vehicle for, after which they replace it with an EV or

an ICEV.

Technological learning. It is a well-documented observation that technology production costs typically decline at a consistent rate over time as cumulative installed capacity increases (Way et al., 2022), a pattern also verified for EV batteries (Weiss et al., 2019). This relationship is represented by the experience curve, mathematically defined as:

$$\text{cost}(n) = \text{cost}(n_1) \times N^b \quad (1)$$

$$LR = 1 - 2^b \quad (2)$$

With $\text{cost}(n)$ the production costs of the n_{th} unit, $\text{cost}(n_1)$ the production cost of the first unit, N the cumulative production, and b the learning index. **Equation (2)** establishes the relationship between the learning index b, which is negative in the case of decreasing costs, and the learning rate LR, which represents the percentage reduction in unit cost for each doubling of production. The experience curve is a widely used forecasting tool (Louwen et al., 2020) and is also applied in our model. We assume the disruptive events to have global influence, so that the country-specific growth rates match global growth rates, establishing a direct relationship between EV adoption in our model and EV prices according to **Equation (1)**.

Our model incorporates the current annual learning rate of 7.5%, as observed in EV market development from 2013 to 2020 (Barwich et al., 2025). We expect this rapid price decline to level off as EV prices approach those of equivalent ICEVs. Following estimates on the difference between equivalent EVs and ICEVs from (Z. Liu et al., 2021), we project final price points at approximately €8,000 for small EVs, €29,000 for medium EVs, and €80,000 for large EVs.

In our model, the range of each available EV type increases linearly over time, adding 10 km of range annually. While EV ranges are unlikely to increase linearly indefinitely, this assumption aligns with observed trends (IEA, 2026). To prevent unrealistically large range projections, we impose maximum range limits of 600 km for small EVs, 660 km for medium EVs, and 730 km for large EVs.

Consumer agents. Our model includes a single agent type representing individual consumers, with each agent corresponding to a unique survey participant. At initialisation, the model creates 537 agents for the U.S., 508 for Germany, and 485 for South Africa, corresponding to the participants in our experimental study who completed both waves. These agents are placed within a stylised environment for each country, consisting of a central urban region and an outer rural region. Initial values for car ownership and psychological characteristics are directly derived from survey responses and analyses. These characteristics are parameterised using data from the DCEs on EV adoption under scenarios with and without disruption.

Combining the DCEs with direct questions on subjective probabilities and affective responses, we estimate the impact of changes in individual and contextual factors on adoption decisions using a multilevel logistic model. The estimated coefficients from this model inform the adoption decision variables for each agent, which are subsequently integrated into a threshold adoption model.

At the start of each time step (representing one year), technological characteristics including price and range are updated. The number of EV adopters among agents within the same income group is used as input for the social norm effect. In random order, the agents for whom it is time to replace their vehicle (as indicated in the survey) then decide whether to adopt an EV or ICEV.

All decision variables are parameterised using survey results. Respondents directly provided values for Subjective Probabilities and Affect toward EVs and ICEVs in the survey. The Importance outcomes and the Social norm effect for each agent were derived from the DCEs, enabling individual estimation of each participant's adoption

preferences.

Our analytical model for agent adoption decision-making is represented by the following equation:

$$\frac{1}{1+e^{-(\alpha_i+\beta_{i,1}x_1+\beta_{i,2}x_2+\cdots+\beta_{i,N}x_N)}} \geq \text{threshold}_{\text{adoption}} \quad (3)$$

With α_i the intercept specific for agent i, β_n the resulting coefficient of agent i for independent variable x_n out of a total of N variables, and the adoption threshold on the right-hand side of the equation. Decision parameters were calibrated through multilevel logistic regression analyses. We constructed separate multilevel logistic regression models for each EV size category: small, medium, and large. To address the repeated measures design of the adoption task, we included a random effect for subjects in the model. Furthermore, to capture individual variability in the importance assigned to different technology attributes, we incorporated random slopes for investment cost, savings, range, public charging infrastructure, and peer effects within this random effect. When a disruptive scenario is activated in the model, the agent decision function is based on the coefficients estimated from the DCE results from Wave 2.

To establish the thresholds for the adoption models, we employed a four-step process. First, we produced model classifications across a range of decision cut-offs. Second, we generated confusion matrices for each cut-off by cross-tabulating the model's classifications with observed choices. Third, we calculated the Matthews Correlation Coefficient (MCC) for each confusion matrix to evaluate model performance. Finally, we selected the threshold that maximised the MCC value.

5.1.2.5 Output

To quantify the impact of the individual policies on EV adoption of policy outcomes, we code the implementation of the policies in each scenario as binary and link these to the simulated EV adoption (total and across income groups), mean policy support, and mean perceived fairness of policy outcomes through a linear model:

$$\text{output}_i = \beta_0 + \sum_{n=1}^{n} \beta_n \cdot \text{policy}_n + \varepsilon \quad (4)$$

With output_i the specific output indicator of interest, β_n the regression coefficients for all the N policies, policy_n a variable that equals 1 if policy n is implemented and 0 if it is not implemented, and ε an error term. Note that this linear model is not used as an input to the simulation model but rather to analyse the simulation output.

5.1.3 Results

5.1.3.1 Discrete choice experiment

Figure 5.3 shows the number of times participants chose an EV across 18 choice tasks in baseline (Wave 1) and disruption (Wave 2) scenarios. The distribution of EV choices resembles a normal distribution across all three countries, but the mean and spread differ markedly. The German sample has the highest degree of EV scepticism, with a large peak of participants rejecting every EV offer. The U.S. shows a substantial rejection peak as well, but participants more frequently adopt EVs overall. South Africa shows the greatest EV enthusiasm, with a higher mean number of accepted offers and the only country where acceptance of all offers exceeds rejection of all offers. Importantly, this distribution does not only reflect adoption preferences under current market conditions, but also under more and less favourable conditions. The average DCE scenario might differ in its proximity to current conditions between countries. The disruption scenarios produce mixed effects: the mean shifts downward in the U.S. and Germany but upward in South Africa. Furthermore, the number of participants rejecting all offers

decreases in the U.S. and South Africa but remains stable in Germany.

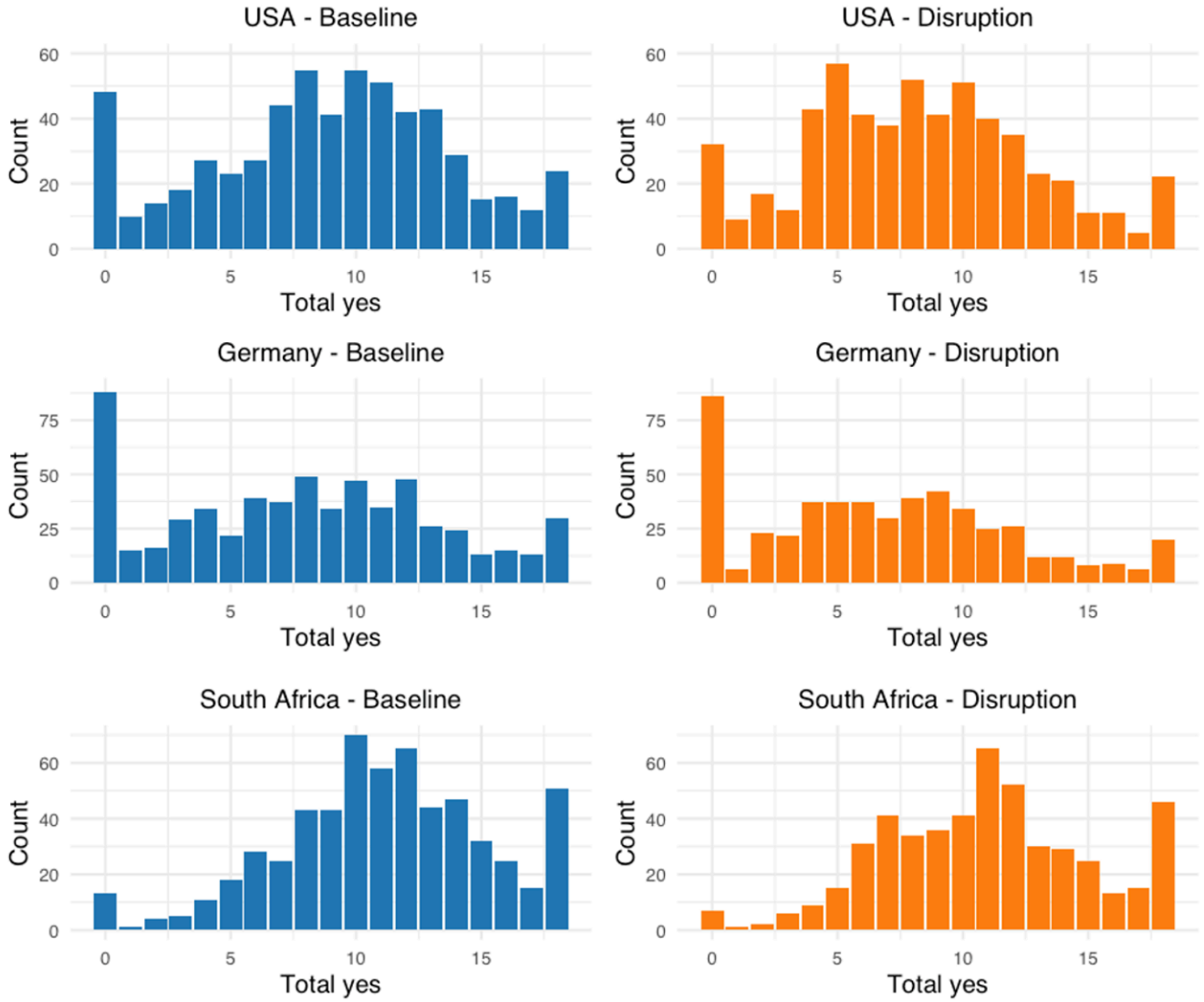

Figure 5.3. Distribution of number of "yes" responses to adopting an EV across the 18 choice tasks of the experiment

Figure 5.4 presents the multinomial logit model coefficients for both waves. The strongest predictors of EV choice are purchase price, fuel and electricity costs, range, vehicle size (except South Africa), and EV affect (except South Africa). Germany stands out in that government trust also significantly influences EV choice. Results remain largely consistent between waves, with notable exceptions. Purchase price becomes a stronger predictor in disruption scenarios, indicating heightened price sensitivity when tariffs are included in the purchase price. Moreover, gasoline and electricity costs lose predictive power, suggesting respondents struggle to evaluate uncertainty ranges and price variability. As an exception, electricity costs maintain similar effects in the German sample across both waves.

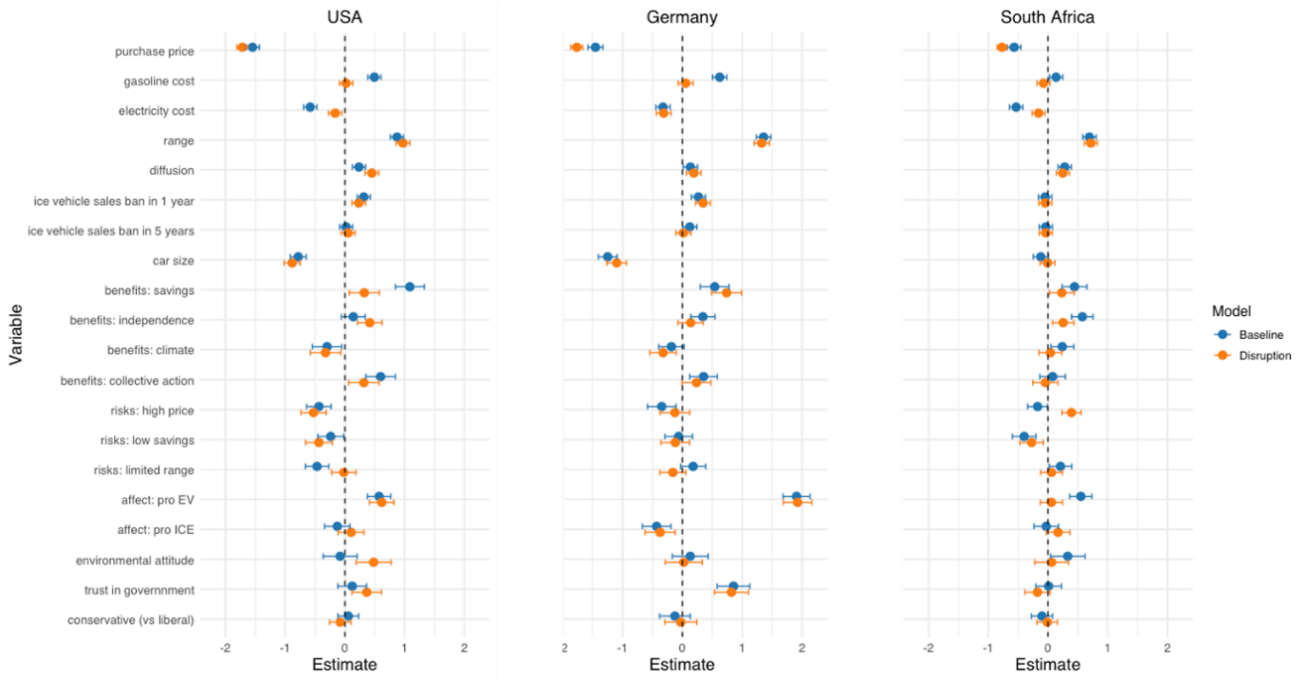

Figure 5.4. Results of the multinomial logit model of the discrete choice experiments.

5.1.3.2 Agent-based model

Figure 5.5 presents 768 EV diffusion scenarios across combinations of three policies: a €5,000 purchase subsidy, a €7/100 km carbon tax, and an ICEV sales ban beginning in 2030; and three disruption settings: 50% EV import tariffs, 100% electricity price fluctuations, and 100% gasoline price fluctuations. All scenarios show rapid EV adoption growth until approximately 2032, after which diffusion slows. Without an ICEV sales ban, adoption reaches 45-75% by 2040. Substantial deviations between disruption and baseline scenarios demonstrate that these disruptions have both positive and negative impacts on EV diffusion.

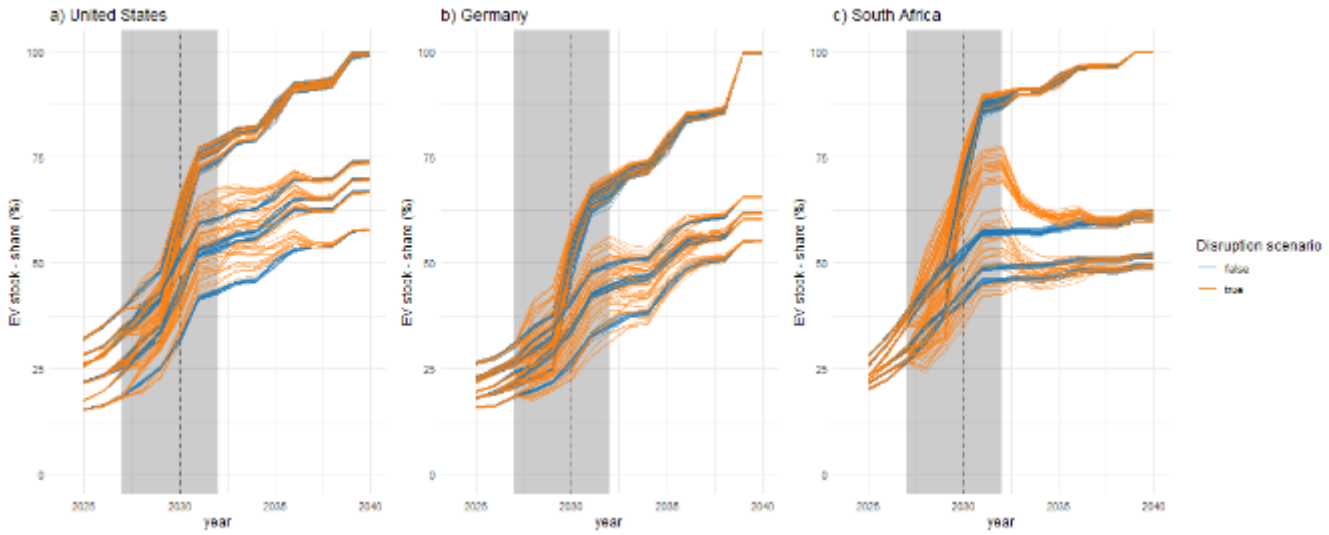

Figure 5.5. EV diffusion scenarios across policy and disruption settings for each of the three countries.
The grey area represents the time period during which disruption events were activated in the disruption scenarios. The dashed vertical line indicates when the ICEV sales ban was implemented in scenarios were that was activated.

Figure 5.6 illustrates policy and disruption impacts across countries over time. Subsidy and tax effectiveness first increase, peaking around 2027-2028, then decline. In baseline scenarios, subsidy and tax impacts are comparable

between the U.S. and Germany, whereas South Africa shows substantially higher subsidy effectiveness. The sales ban achieves greatest effectiveness in South Africa, where, compared to the other two countries, adoption remains lower without it. Among disruptions, tariffs produce the largest negative effect on adoption, followed by electricity cost fluctuations. Gasoline price fluctuations have minor impacts. Disruption effects persist several years beyond 2032 but largely disappear by the late 2030s.

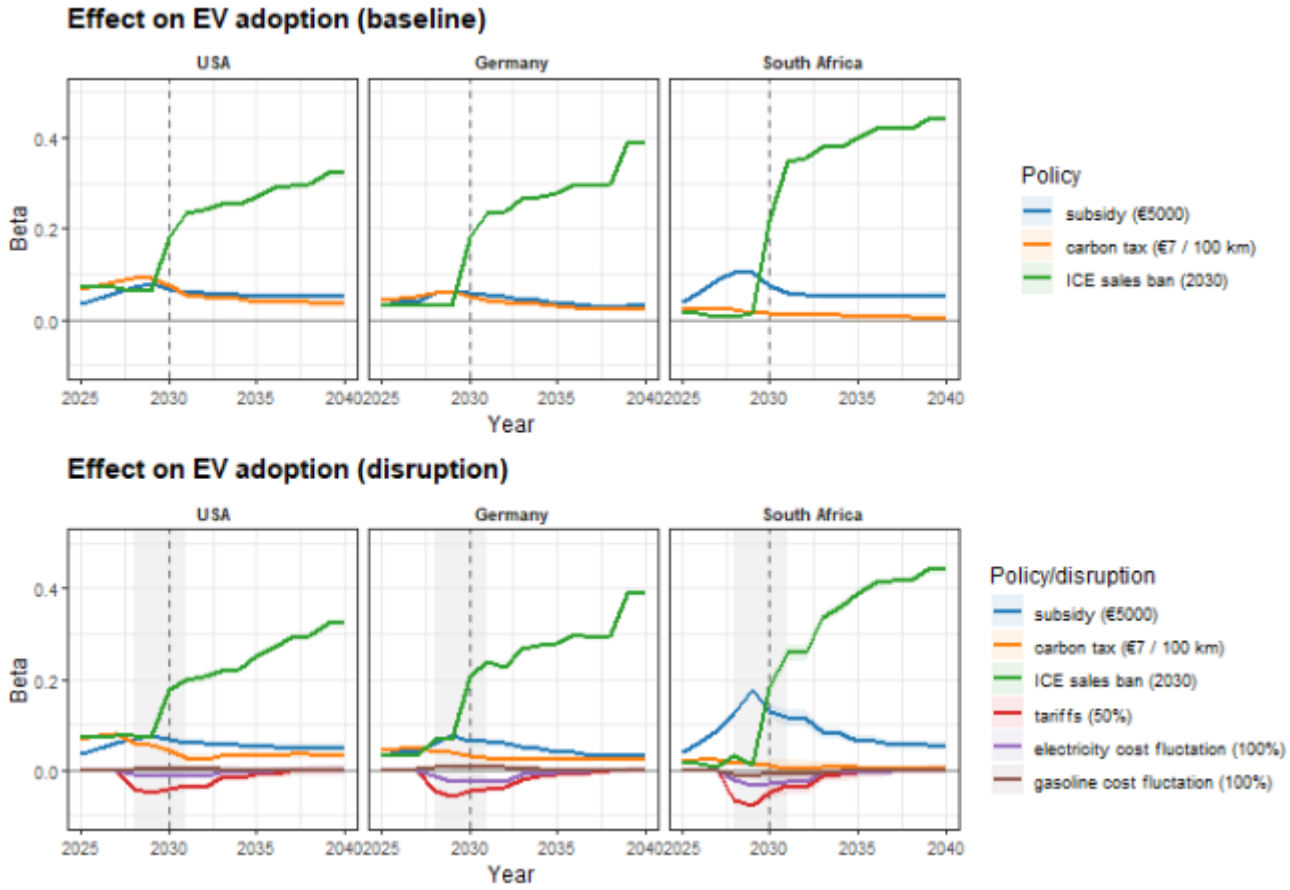

Figure 5.6. Regression coefficients of the increase of EV stock share under different policy mixes and disruption scenarios, calculated separately for each simulation year.
The grey area represents the time period during which disruption events were activated in the disruption scenarios. The dashed vertical line indicates when the ICEV sales ban was implemented in scenarios were that was activated.

Figure 5.7 shows how policy effectiveness changes during disruption. Subsidies become more effective during and after disruption in Germany and South Africa, whereas effects fluctuate between positive and negative in the US. Carbon tax effectiveness declines in all countries during disruption, though its impact remains minimal in South Africa. The ban's anticipated effect is larger in early disruption years, whereas its actual implementation effect is smaller.

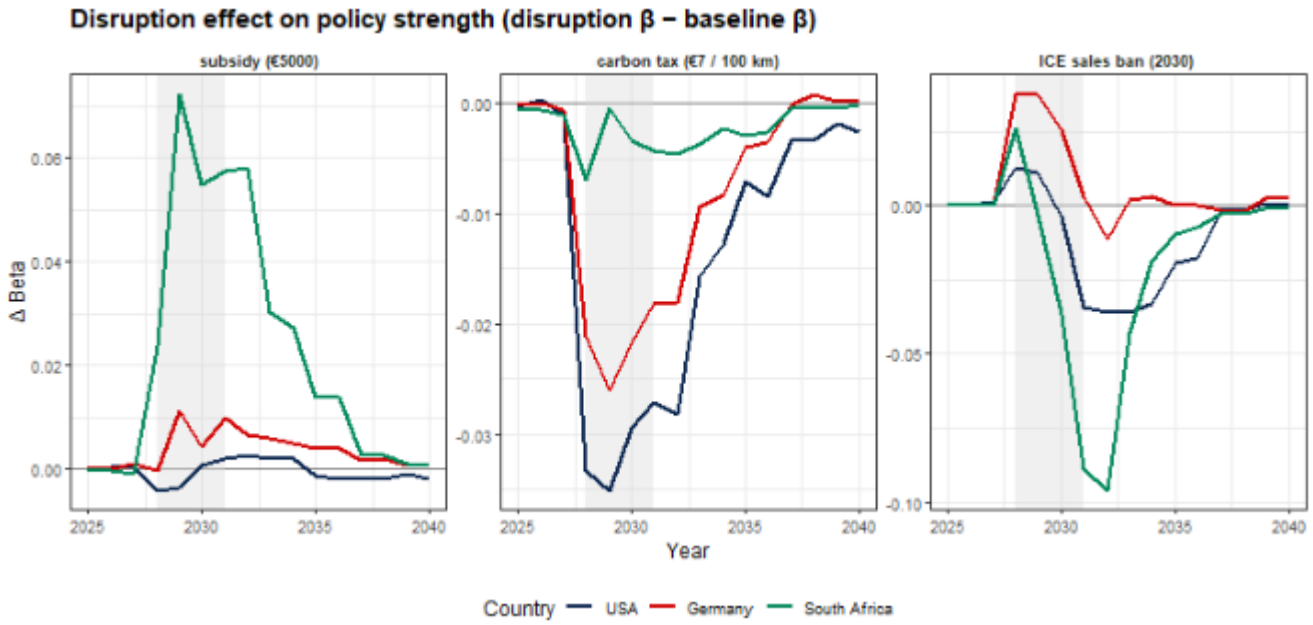

Figure 5.7. Difference regression coefficients of the increase of EV stock share for the different policies with and without disruption scenarios, calculated separately for each simulation year.
The grey area represents the time period during which disruption events were activated in the disruption scenarios. The dashed vertical line indicates when the ICEV sales ban was implemented in scenarios were that was activated.

Figures 5.8 and 5.9 examine EV adoption heterogeneity across income quintiles. Overall, higher income groups adopt EVs at greater rates, but patterns vary considerably. In Germany, Q5 initially is among the highest adoption groups, but drops below Q3 and Q4 mid-diffusion before recovering. In South Africa, Q3 adoption remains lowest in the non-disruptive scenarios, but overtakes Q1 in scenarios with disruption. Figure 5.9 shows that disruptions increase adoption inequality in Germany and South Africa but decrease it in the US.

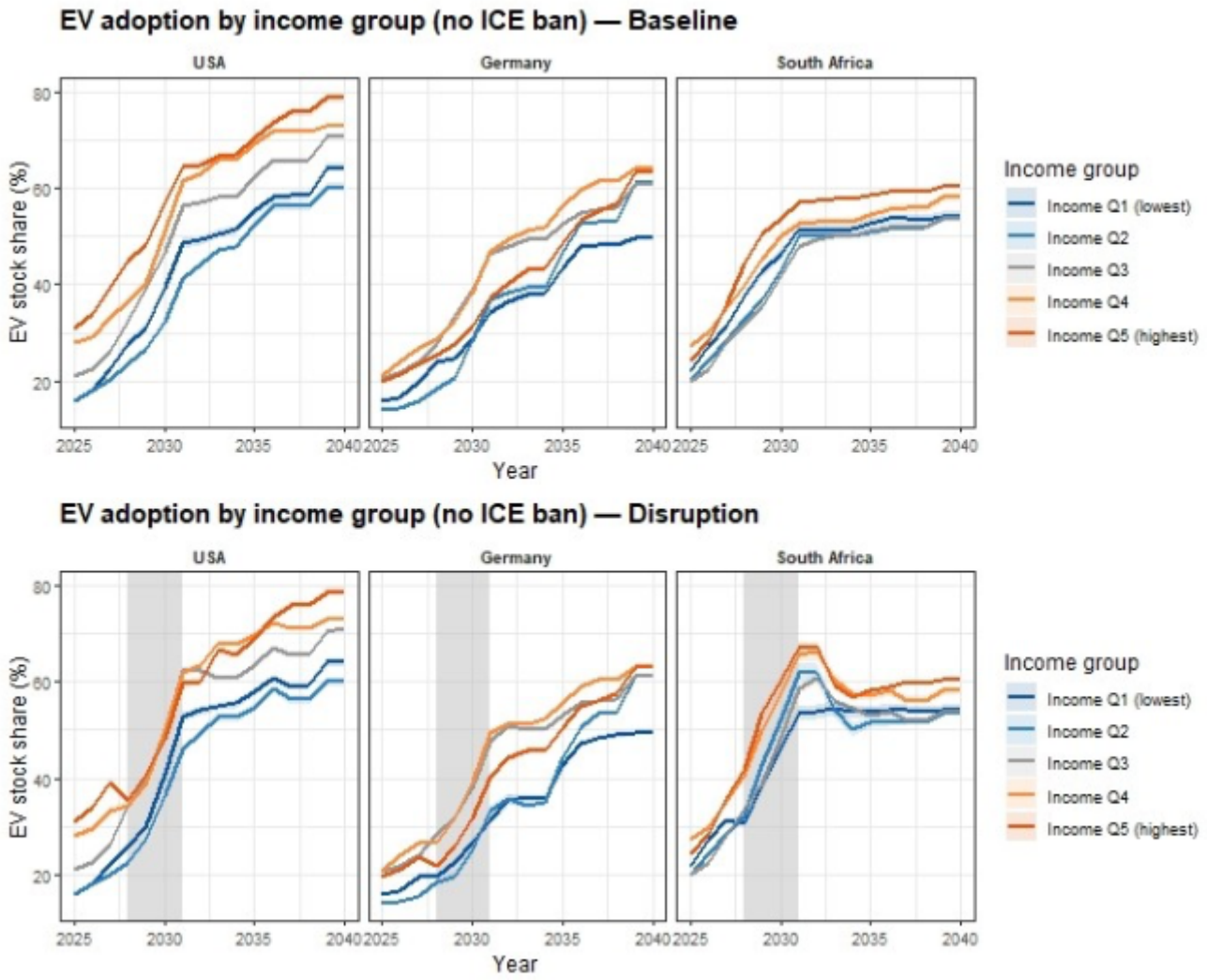

Figure 5.8. Increase in EV stock share under different policy mixes and disruption scenarios, calculated separately for each simulation year.

The grey area represents the time period during which disruption events were activated in the disruption scenarios. The scenarios with the ban are excluded, given that the ban has the same impact for all the income groups.

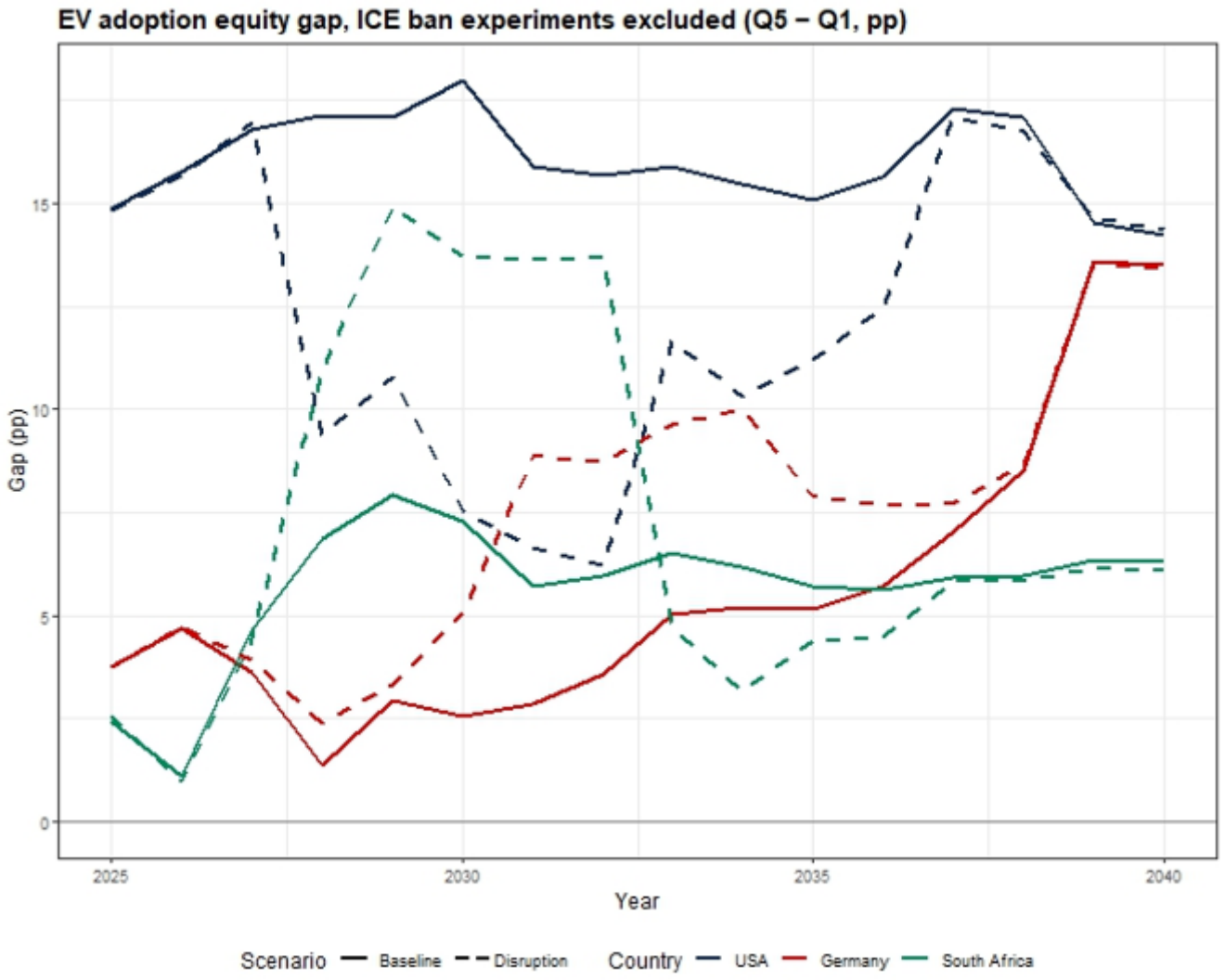

Figure 5.9. Difference in EV adoption between high (Q5) and low (Q1) income groups.
The scenarios with the ban are excluded, given that the ban has the same impact for all the income groups

The ABM provides important insights into EV adoption dynamics within specific countries, including income-specific diffusion and policy effects. However, it does not allow market interactions between countries or assessing the broader system-level implications, such as emissions and energy production, of different EV adoption rates. In the following subsections, we describe an approach to link adoption data like the ABM output with IAMs to estimate system-level implications of EV diffusion and derive recommendations for policymakers and modellers.

5.2 Behavioural module and soft-link

The general idea of the behavioural module is to provide realistic boundaries for technology adoption based on psychological data (e.g., social norms), contextual factors (e.g., GDP), and technological characteristics (e.g., costs) represented in IAMs. Based on collecting experimental and survey data, we are able to create behavioural module versions that provide behavioural adoption boundaries for different population groups (defined by their psychological and socio-demographic characteristics as well as country or region of residency) at different points in time, given different contextual conditions (including technology characteristics, and country-level factors like temperature and infrastructure). When corresponding data is available, the structure of the behavioural module allows its application to various technologies (e.g., heat pump adoption) and behaviours (e.g., adopting a vegetarian diet). Here, we focused on one climate-relevant behaviour – EV adoption – and used the corresponding

data to create IAM-specific behavioural module versions with different resolutions regarding geography and technology characteristics. Furthermore, we combine the baseline behavioural module (extensively described in Deliverable D4.6) with the experimental data described in Section 5.1 to create behavioural module versions for various disruptive event scenarios.

5.2.1 Baseline behavioural module

In the DCE underlying the baseline behavioural module, the outcome variable "car choice" is a multinomial variable with five response options (Cars 1-4 and none of the cars). Hence, we used multinomial mixed-effect models to estimate the adoption rate boundaries necessary for establishing soft-links with the IAMs. A converged multinomial mixed effect model allows the estimation of adoption rates for every possible combination of DCE attributes (and for every possible population group defined by psychological and socio-demographic variables, as well as changing country characteristics) based on the regression coefficients. Because IAMs currently do not represent actor heterogeneity, we focused solely on the DCE attributes as well as EV diffusion at the country level as EV adoption predictors. However, although consumer heterogeneity is hidden in the current formulation of the behavioural modules, the adoption estimates implicitly reflect the heterogeneity that our underlying analyses revealed (see Deliverable D4.6). The adoption estimates together with the corresponding confidence intervals as well as the conditions that produced them (i.e., the car and context attributes) can be compiled in a table (see Figure 5.10 for an example). Importantly, when an IAM does not include a specific car or context attribute (e.g., battery range or charging infrastructure), the estimates can be averaged across this attribute, leading to larger confidence intervals for a specific car-context combination.

Year	Country	Purchase price EV	Purchase price ICEV (petrol)	Purchase price ICEV (diesel)	Electricity costs (/100km)	Petrol costs (/100km)	Diesel costs (/100km)	Diffusion in country (at t-1)	EV range	Carbon reduction potential (EV)	Charging infrastructure	EV Adoption Rate	
												Lower Bound	Upper Bound
2025	Austria	40'800 €	13'600 €	13'600 €	3,80€	5,80€	4,00€	10%	200km	30%	low	0%	1%
2025	Austria	40'800 €	13'600 €	13'600 €	3,80€	5,80€	4,00€	10%	200km	30%	medium	1%	3%
2025	Austria	40'800 €	13'600 €	13'600 €	3,80€	5,80€	4,00€	10%	200km	30%	high	2%	3%
2025	Austria	40'800 €	13'600 €	13'600 €	3,80€	5,80€	4,00€	10%	300km	30%	low	1%	2%
2025	Austria	40'800 €	13'600 €	13'600 €	3,80€	5,80€	4,00€	10%	300km	30%	medium	2%	4%
...	...	...	...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2100	UK	£16400	£49300	£49300	£3,10	£12,70	£10,90	60%	500km	70%	medium	75%	80%
2100	UK	£16400	£49300	£49300	£3,10	£12,70	£10,90	60%	500km	70%	high	76%	82%
2100	UK	£16400	£49300	£49300	£3,10	£12,70	£10,90	60%	700km	70%	low	80%	86%
2100	UK	£16400	£49300	£49300	£3,10	£12,70	£10,90	60%	700km	70%	medium	82%	88%
2100	UK	£16400	£49300	£49300	£3,10	£12,70	£10,90	60%	700km	70%	high	84%	88%

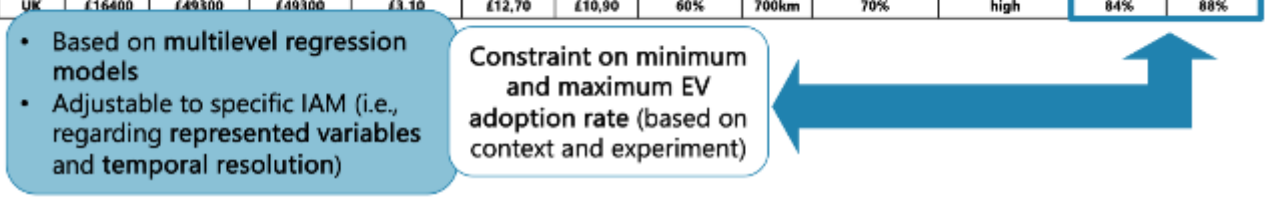

Figure 5.10. Exemplary Output Table based on Behavioural Module

5.2.2 Disruptive event behavioural module

The disruptive event versions of the behavioural module have the same structure as the baseline version of the module. However, the underlying estimations are adjusted to account for how the disruptive events affect technology costs and decision-making. These adjustments are made based on the German data collection and the multinomial mixed effect models presented in Figure 5.4. We used Germany because we focused on the European context for the soft-links. So, estimates from the U.S. and South Africa are less applicable.

We differentiate between two different types of disruptive events that vary in how they affect the estimations underlying the behavioural module: tariffs on EVs and uncertainty in gasoline and electricity prices. Tariffs have

two separate effects. First, they increase the actual technology costs of EVs. This is represented in the underlying model by multiplying EV purchase costs represented in the IAMs by one plus the tariff level. We test the effect of three different tariff levels (25%, 50%, 75%) so we multiplied the purchase costs by 1.25, 1.5, and 1.75. Given that higher purchase prices lead to lower adoption rates, we assume that tariffs will reduce EV adoption rates. Second, the presence of tariffs made participants weigh purchase prices more strongly in their decisions (i.e., the purchase price had a stronger effect on adoption decisions). We account for this mechanism by adjusting the country-specific regression coefficients from the baseline module uniformly based on how the regression coefficient changed in Germany when tariffs were included (Figure 5.4; around 21.5% stronger regression coefficient). Both tariff-based adjustments were only implemented, when the disruptive event included an EV tariff.

Uncertainty in gasoline and electricity prices affected only the effect of operating costs of gasoline vehicles and not EVs in Germany. Introducing uncertainty led to people not considering gasoline prices in their adoption decisions, while they still integrated EV operating costs in their decisions in the same way as without uncertainty. We therefore adjusted the regression model underlying the baseline behavioural module by setting the regression coefficients of the operating costs for gasoline and diesel vehicles to 0, when a disruptive event also included price uncertainty. We extended the finding from Figure 5.4 for gasoline vehicles to diesel vehicles because they are conceptually closer to gasoline vehicles than to EVs (e.g., you must drive to the gas station to fuel diesel; diesel and gasoline prices are presented in the same way at gas stations). Because higher operating costs lead to more EV adoption in the baseline behavioural module, we assume that uncertainty in gasoline and electricity prices will lead to lower EV adoption.

5.2.3 Soft-linking behavioural modules with IAMs

We follow a two-step soft-linking procedure to increase the realism of how EV adoption is modelled in IAMs (for an overview, see Figure 5.11). The first step – a prerequisite step that enables the soft-link – is making sure that the DCE and the IAMs have shared technical assumptions. For example, purchase prices included in the DCE should cover the range of technology costs in the IAMs. Prior to designing the experiment, we approached the modelling teams and asked which EV attributes and what levels of these attributes are represented in the IAMs in order to adjust the attribute levels of our experiment accordingly. The idea was not to perfectly mirror each level, but to cover the whole range accounted for in the IAMs (e.g., minimum and maximum purchase price of EVs) as we can extrapolate adoption rates for values in between. We needed to make some additional adjustments and add attributes that are currently not represented in all IAMs (e.g., range of EVs and ICEVs) to increase the external validity of our experiment. For example, even though some IAMs only include monetary drivers, excluding battery range in the choice experiment would neglect a large body of research demonstrating the importance of this attribute for the purchase decision (Wicki et al., 2023). In addition, participants received different attribute levels in the DCE depending on the car size (small, medium, large) that they usually prefer. Both the purchase price and the operating costs increased with increased car size.

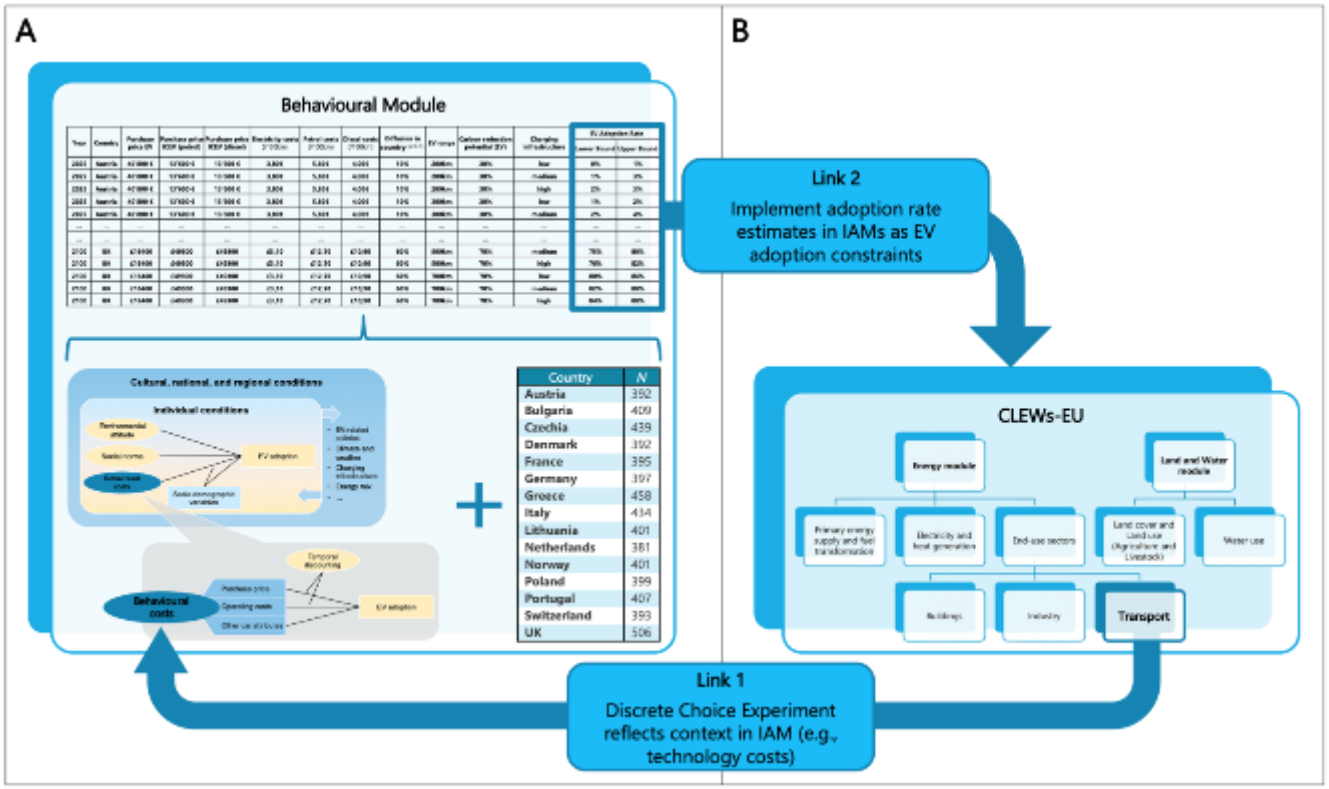

Figure 5.11. Schematic Visualisation of Soft-Linking Procedure with CLEWs-EU.
Part A describes the data collection and part B the integration on this data collection into CLEWs-EU.

After ensuring that the attribute levels align with IAM assumptions, we ran the experiment and assessed the various adoption drivers at different levels in 15 European countries (see Figure 5.11A). Compared to Deliverable D4.6 the data collection now also includes the two-wave experimental study outlined in Section 5.1. Based on the resulting data, we calculated EV adoption rate estimates for all possible car-context combinations under the baseline assumptions (i.e., 15-country study) and under various disruptive event scenario assumptions (i.e., adjustments to the baseline assumptions based on two-wave study in Germany). We can even go beyond the levels assessed in the experiment by treating the attributes as numeric variables (and not ordered categorical variables) in the underlying mixed effect models. The resulting IAM-specific input-output tables (input being the car and context attributes and output being the potential range of EV adoption rates given these attributes) serves as the second part of the soft-link with the IAMs (see Figure 5.11B). The output part of the table informs a novel parameter in the IAM, namely a constraint parameter on the EV adoption that depends on the specific contextual characteristics in the IAM at a specific time step (e.g., purchase price of EVs in 2050). This constraint parameter limits EV adoption at that time step to a rate within the lower and upper bounds. The link requires that the row in the behavioural module input-output tables is chosen that resembles the context of the IAM at this time step.

The behavioural modules also include a dynamic aspect by accounting for the effect of social norms. This makes the linking more difficult as our operationalisation of social norms constitutes a descriptive social norm (current EV diffusion in a country), which is time sensitive and usually refers to the diffusion at the time of purchase. At the same time, we want to estimate this diffusion based on the context, including the descriptive norms (see Figure 5.12). To refrain from having to estimate adoption rates twice, and in light of the prolonged decision phase in car purchases (Klöckner, 2014), we calculate the adoption rate at any given time t, based on the adoption rate from the previous time step (i.e., t-1) as the social norm. The obvious caveat with this approach arises when the temporal resolution of an IAM is rather low (e.g., 5 years), as the adoption rate at t-1 is outdated and not behaviourally relevant in this scenario. We suggest the following solution: assuming linear changes in contextual conditions (i.e.,

technology costs, fuel costs, electricity costs) between t-1 and t, we estimate the adoption rates in the intermediate years based on the contextual conditions as well as the descriptive norm in the previous year. Therefore, we account for the dynamism of the social context (and allow for non-linear adoption trends due to this dynamism). We did not use the effect of the descriptive norm DCE attribute to predict EV adoption rates (because the results were not in line with previous literature; Günther et al., 2025), but rather the effect of country-level EV diffusion (the effect does not vary across countries), as it was in line with our hypotheses.

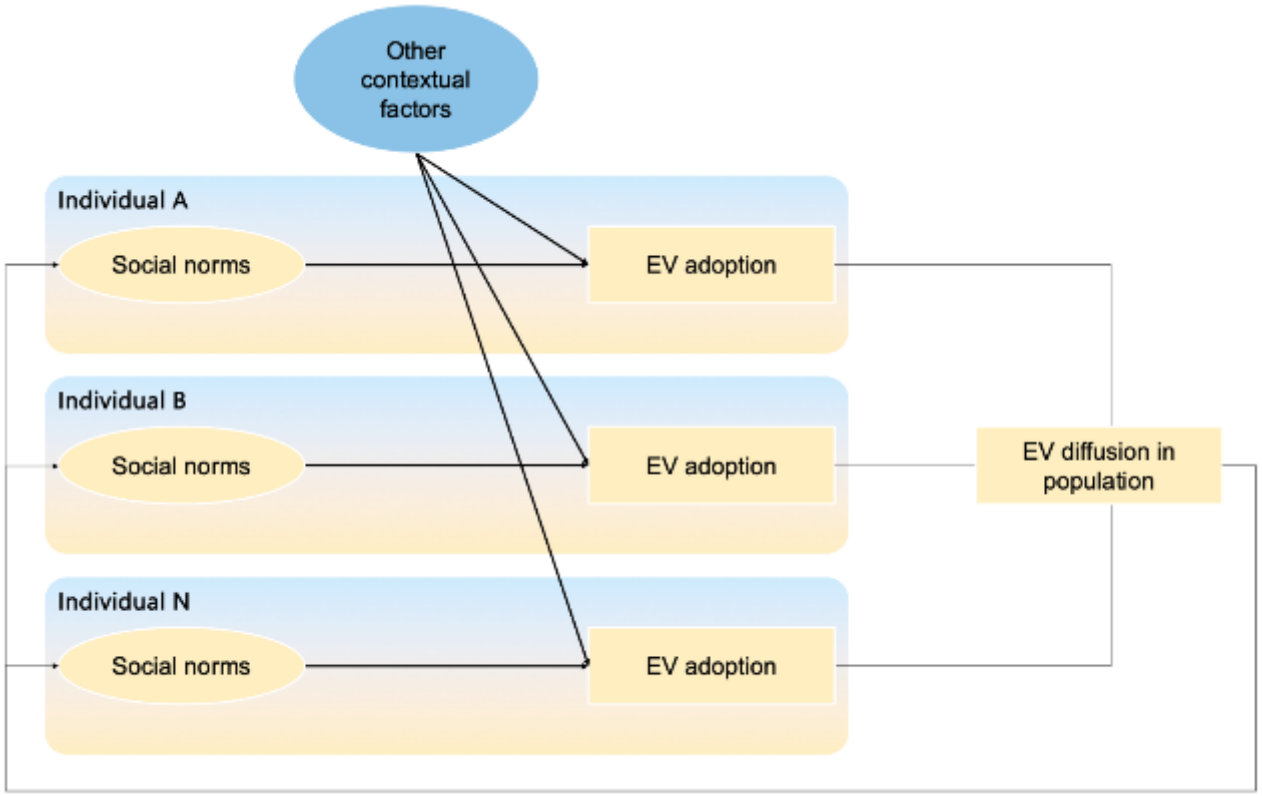

Figure 5.12. Visualisation of the Social Norm Dilemma.
In an ideal world the social norm at a specific timepoint would be equal to the EV diffusion in the population at that same timepoint, but we need one of them to calculate the other.

An additional challenge lies in the geographical distribution of our sample, which only includes 15 European countries due to budgetary constraints. A cluster analysis reported in Deliverable D4.6 ensured that we included at least one representative country per cluster. This approach allowed us to extrapolate our findings to the countries that were not included in the data collection from the country that is representative for the respective cluster. When multiple countries from one cluster are included in the sample, we chose the one that is nearest to the excluded country in the multivariate space underlying the cluster analysis (i.e., closest regarding GDP, climate change vulnerability, income inequality, and previous country classifications).

Finally, the behavioural module-based input-output tables are customised for each IAM depending on which car and context attributes they represent as well as their geographical resolution. A more detailed description of which IAM assumptions were updated and the IAM-specific behavioural module configurations can be found in Deliverable D4.6. We want to highlight again that the behavioural module versions presented here have the potential to deliver adoption rate estimates for specific population groups not only based on socio-demographic but also psychological characteristics. The potential of this flexibility can only be explored when IAMs themselves represent heterogeneity in the actors.

5.3 Soft-link results

All model outputs from the IAM runs that include a soft-link with a behavioural module are compared to an IAM run that does not include the soft-link. The scenario that is held constant across all IAM runs is the DIAMOND baseline scenario, which is characterised by a carbon emission target of reaching Net Zero by 2050. Therefore, emissions are expectedly very similar between IAM runs without and with the soft-link by 2050, but which sectors emissions are mitigated may vary significantly between these model runs. We run nine different scenarios for each IAM; one scenario without any soft-link and eight soft-link scenarios with different versions of the behavioural module: baseline (i.e., no disruptive event), a 25% tariff on EVs and no uncertainty in gasoline and electricity prices, a 50% tariff and no uncertainty, a 75% tariff and no uncertainty, no tariff and uncertainty, a 25% tariff and uncertainty, a 50% tariff and uncertainty, and a 75% tariff and uncertainty.

5.3.1 CLEWs-EU

For CLEWs-EU, we focus on four sets of model outcomes: EV diffusion, CO_2 emissions (total and transport), carbon capture and removal, and electricity supply. All nine scenarios are compared for the 27 modelled countries and the EU-27 aggregate (sum across countries) over the modelling horizon 2021 to 2055. EV diffusion is measured as the share of EVs in total passenger-car activity.

Figure 5.13 shows the EU-27 results. The behavioural soft-link mainly changes the timing of EV adoption. In the DIAMOND baseline scenario without soft-link, EVs account for less than 1% of passenger-car activity in 2025 and 8% in 2030, after which adoption accelerates steeply to 74% in 2055. With the baseline soft-link, the EV share is already 21% in 2025 and 43% in 2030, but then grows more slowly, with temporary dips in 2035 and 2050, and reaches 60% in 2055. The run without soft-link overtakes the soft-link around 2050, which is most likely the result of EVs being a relatively cheap decarbonization technology under emission target. As hypothesised, all disruptive events shift the diffusion curve downwards. In 2050, EV tariffs of 25%, 50% and 75% reduce the EV share to 46%, 39% and 32%, respectively; price uncertainty alone reduces it to 42%. Combining tariffs and price uncertainty leads to the strongest attenuation, with the 75% tariff and uncertainty scenario reaching only 22% in 2055.

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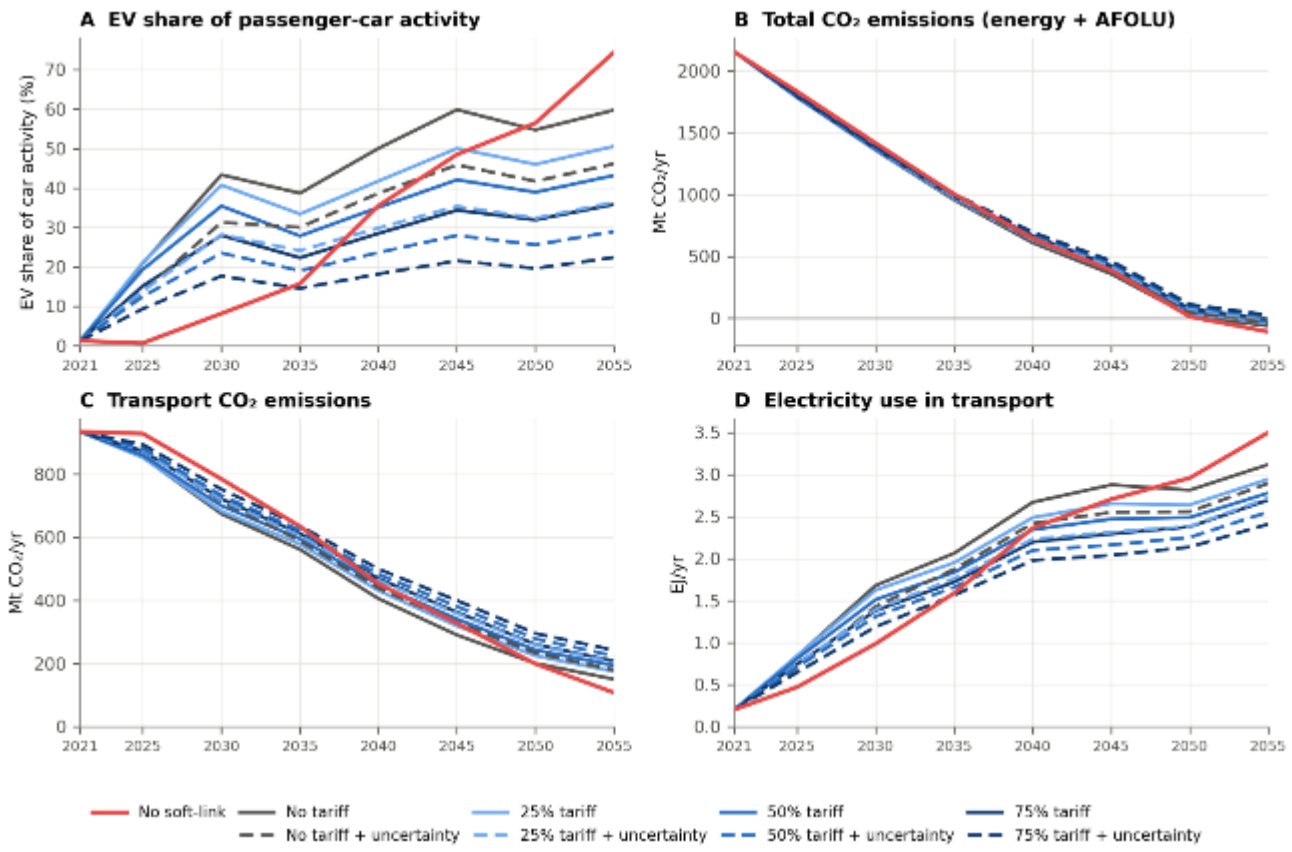

Figure 5.13. CLEWs-EU – EU-27 Results: Baseline vs. Soft-Link.
(A) EV share of passenger-car activity, (B) total CO_2 emissions (energy and AFOLU), (C) transport CO_2 emissions and (D) electricity use in transport. Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices. See Figures A5.5 and A5.6 for a more detailed look at electricity generation.

Figure 5.14 shows that the soft-link effect differs across countries. In Bulgaria, Poland, Portugal, Slovakia and Slovenia, EV adoption remains below 1% until at least 2045 in the run without soft-link (probably reflecting that there are cheaper decarbonization alternatives in other sectors than EVs), whereas the baseline soft-link yields EV shares of 27% to 50% already in 2030. In most other countries, EV adoption increases in both runs but at different speeds: the soft-link leads to higher adoption in early years, while the run without soft-link catches up later and exceeds the baseline soft-link by 2055 in 19 of the 27 countries (e.g., Austria, Belgium, Germany and Denmark). Under the baseline soft-link, EV shares in 2055 range from 34% (Slovenia) to 79% (Denmark), reflecting the heterogeneous purchase-price, fuel-cost and social conditions across countries. The overall order of EV adoption in the disruptive events is the same across countries, but magnitude of differences between disruptive scenarios varies (e.g., larger spread in Austria compared to Sweden).

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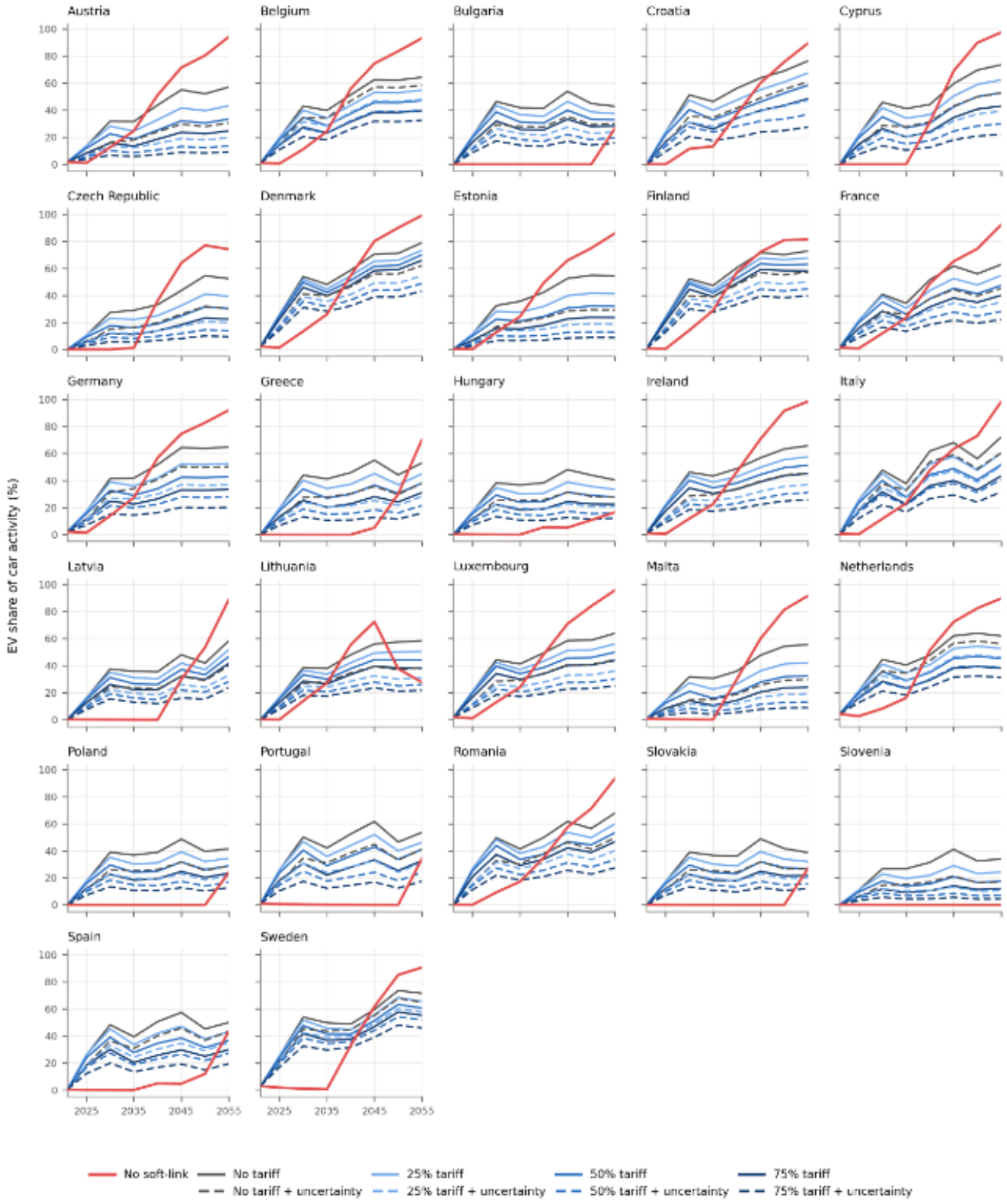

Figure 5.14. CLEWs-EU – EV Share of Passenger-Car Activity by Country: Baseline vs. Soft-Link.
Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

The diffusion patterns translate into transport emissions (Figure 5.13C; country results in Figure A5.1). In 2030, the baseline soft-link reduces EU-27 transport CO_2 emissions from 784 to 674 Mt CO_2 (−14%) compared with the run

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without soft-link. This advantage shrinks over time; both runs reach about 200 Mt CO_2 in 2050, and by 2055 transport emissions are higher with the soft-link (151 vs. 108 Mt CO_2). All disruptive events lead to less mitigation in the transport sector. In the 75% tariff and uncertainty scenario, transport emissions amount to 752 Mt CO_2 in 2030 and 242 Mt CO_2 in 2055, more than twice the level of the run without soft-link. Correspondingly, electricity use in transport is higher with the soft-link in early years (1.7 vs. 1.0 EJ in 2030) but lower at the end of the horizon (3.1 vs. 3.5 EJ in 2055; Figure 5.13D). Total CO_2 emissions decline in all scenarios and approach net zero around 2050 (Figure 5.13B; Figure A5.2), as all runs are constrained by the same decarbonisation target.

Under an emission target, residual transport emissions must be compensated elsewhere in the system. In this study, the modelling output indicates compensation mainly through carbon capture and removal (Figure 5.15; country results in Figures A5.3 and A5.4). Carbon capture (CCS and direct air capture) is negligible until 2030 and increases to 320 to 380 Mt CO_2 by 2050 across scenarios. It is higher in all soft-link scenarios than in the run without soft-link (322 Mt CO_2 in 2050), increasing from 347 Mt CO_2 with the baseline soft-link to 378 Mt CO_2 in the 75% tariff and uncertainty scenario. This additional capture is almost entirely provided by direct air capture, while bioenergy with CCS (BECCS) in the power sector hardly differs between scenarios (129 to 133 Mt CO_2). Total carbon removal (BECCS, direct air capture and afforestation) is similar for the run without soft-link and the baseline soft-link but increases with the severity of the disruptive event, as both direct air capture and afforestation are expanded.

Taken together, the CLEWs-EU results show that the behavioural soft-link brings EV adoption forward and lowers transport emissions in the near term. Under strict emission targets, EV adoption in the run without soft-link, likely driven by the emission target, is higher at the end of the horizon. Disruptive events substantially attenuate EV diffusion, increasing residual transport emissions and the reliance on carbon capture and removal.

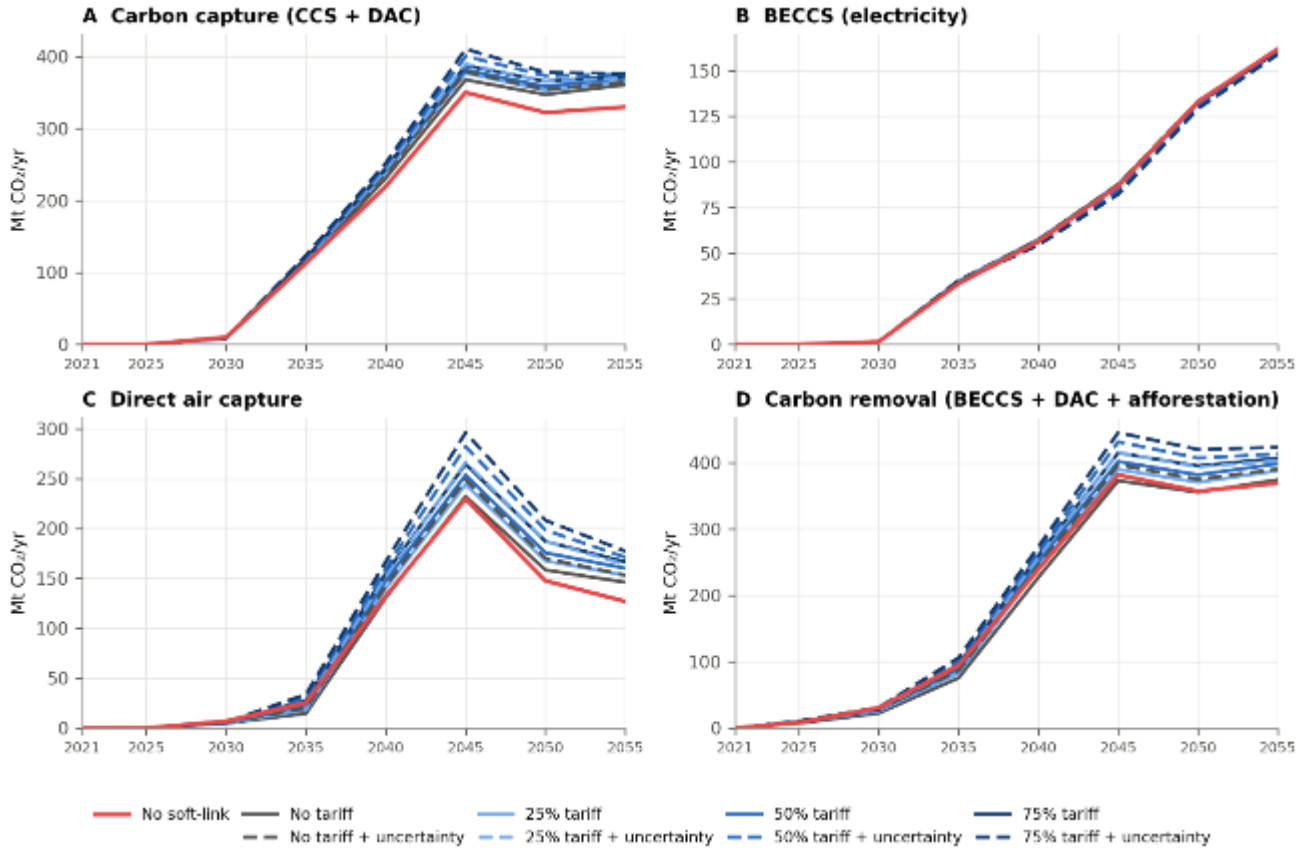

Figure 5.15. CLEWs-EU – EU-27 Carbon Capture and Removal: Baseline vs. Soft-Link.
(A) Carbon capture (CCS and direct air capture), (B) BECCS in electricity generation, (C) direct air capture and (D) carbon

removal (BECCS, direct air capture and afforestation), in Mt CO_2/yr. Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

5.3.2 GCAM Europe

For GCAM Europe, we focus on EV diffusion, total system and transport CO_2 emissions, carbon capture and removal, and CO_2 emissions from energy supply for the 27 EU member states and the EU-27 aggregate over the modelling horizon 2015 to 2050. EV diffusion is measured as the share of battery-electric vehicles (BEVs) in light-duty-vehicle (LDV) passenger-kilometres. Results are reported for the run without soft-link and seven soft-link scenarios; because of initial issues with model convergence, the scenario with price uncertainty only is discussed separately at the end of this section.

Figure 5.16 shows the EU-27 results. The baseline soft-link raises EV diffusion above the run without soft-link throughout the modelling horizon. Compared to the CLEWs-EU results observed before, an important feature that sets the two IAMs apart is the inclusion of a non-monetary preference parameter in GCAM Europe which might be able to explain the attenuated EV diffusion compared to CLEWs-EU without soft-link. Without soft-link, the BEV share of LDV passenger-kilometres increases from 4% in 2025 to 32% in 2050. With the baseline soft-link, it increases to 47% in 2050, about 15 percentage points higher. Disruptive events attenuate this effect: in 2050, EV tariffs of 25%, 50% and 75% reduce the BEV share to 40%, 35% and 30%, respectively, and the combination with price uncertainty reduces it further to 34%, 29% and 24%. The combination of a 75% tariff with price uncertainty leads to lower EV diffusion than in the run without soft-link.

The higher EV uptake under the baseline soft-link is reflected in lower LDV and transport emissions (Figure 5.16C–D; country results in Figure A5.9). In 2050, LDV emissions amount to 91 Mt CO_2 with the baseline soft-link compared with 117 Mt CO_2 without soft-link (−23%), and transport emissions to 348 compared with 375 Mt CO_2. Disruptive events increase residual emissions, with the 75% tariff and uncertainty scenario reaching 129 Mt CO_2 from LDVs and 386 Mt CO_2 from transport in 2050. Total system CO_2 emissions, by contrast, hardly differ between scenarios (Figure 5.16B; Figure A5.8). They decline in all runs and become net negative before 2050, as all scenarios are constrained by the same emission target.

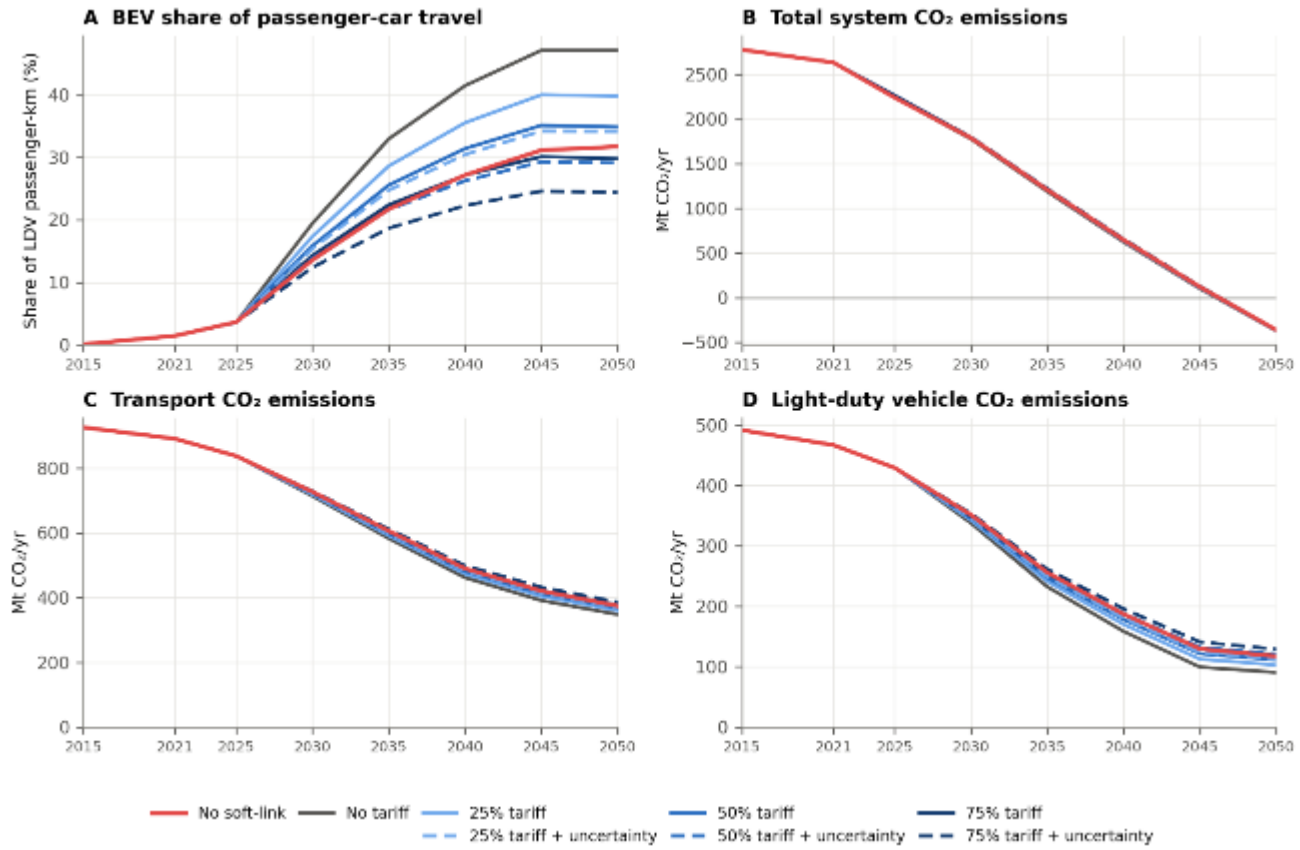

Figure 5.16. GCAM Europe – EU-27 Results: Baseline vs. Soft-Link.
(A) BEV share of LDV passenger-kilometres, (B) total system CO_2 emissions, (C) transport CO_2 emissions and (D) LDV CO_2 emissions. Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices. The price-uncertainty-only scenario is shown separately in Figure A5.13.

Figure 5.17 shows the BEV share by country. In 2050, the baseline soft-link exceeds the run without soft-link in 26 of the 27 countries (the exception being Malta, where both reach about 39%). BEV shares under the baseline soft-link range from 29% (Slovenia) to 54% (Croatia) in 2050, compared with 13% (Romania) to 47% (Estonia) without soft-link. In some countries (e.g., Slovenia, Spain and Sweden), the soft-link produces a peak in EV diffusion around 2040 and 2045, followed by a slight decline. The combination of a 75% tariff and price uncertainty results in lower BEV shares than in the run without soft-link in 20 of the 27 countries by 2050.

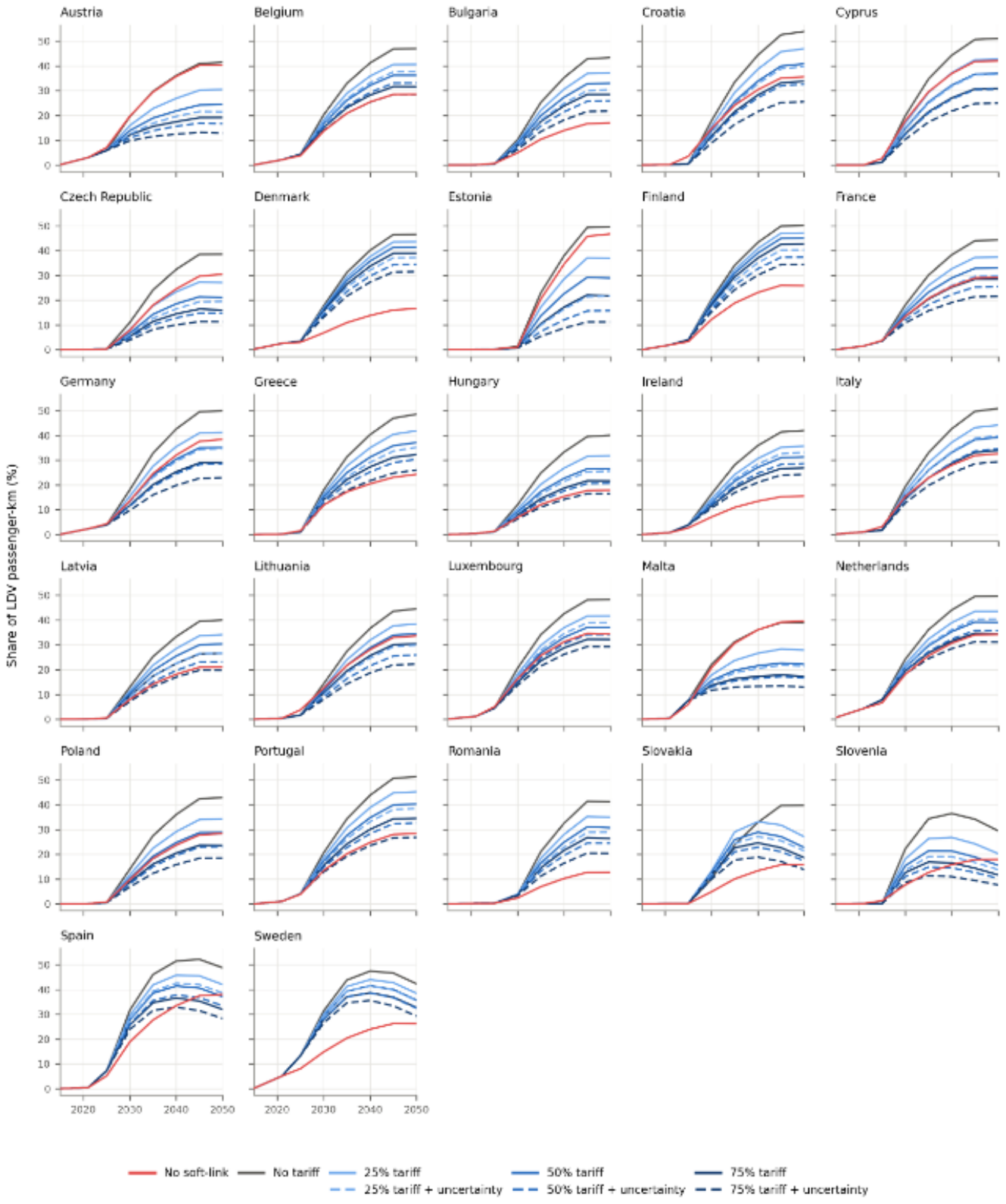

Figure 5.17. GCAM Europe – BEV Share of LDV Passenger-Kilometres by Country: Baseline vs. Soft-Link. Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

As in CLEWs-EU, differences in transport emissions are partly compensated through carbon capture and removal (Figure 5.18; country results in Figures A5.10 and A5.11). Carbon capture increases from about 370 Mt CO_2 in 2030

to 950 to 985 Mt CO_2 in 2050, most of which is stored geologically. With higher EV uptake, less capture is needed: in 2050, carbon capture amounts to 953 Mt CO_2 with the baseline soft-link compared with 972 Mt CO_2 without soft-link, and carbon removal to 918 compared with 936 Mt CO_2. Disruptive events reverse this effect. In the 75% tariff and uncertainty scenario, carbon capture reaches 983 Mt CO_2 and carbon removal 945 Mt CO_2 in 2050, an increase of about 30 Mt CO_2 relative to the baseline soft-link that roughly matches the additional 38 Mt CO_2 of transport emissions in this scenario. This compensation also shows in energy-supply emissions (Figures A5.7 and A5.12), which turn net negative across. They are slightly less negative with the baseline soft-link and more negative in the 75% tariff and uncertainty scenario, mainly due to differences in liquid-fuel production.

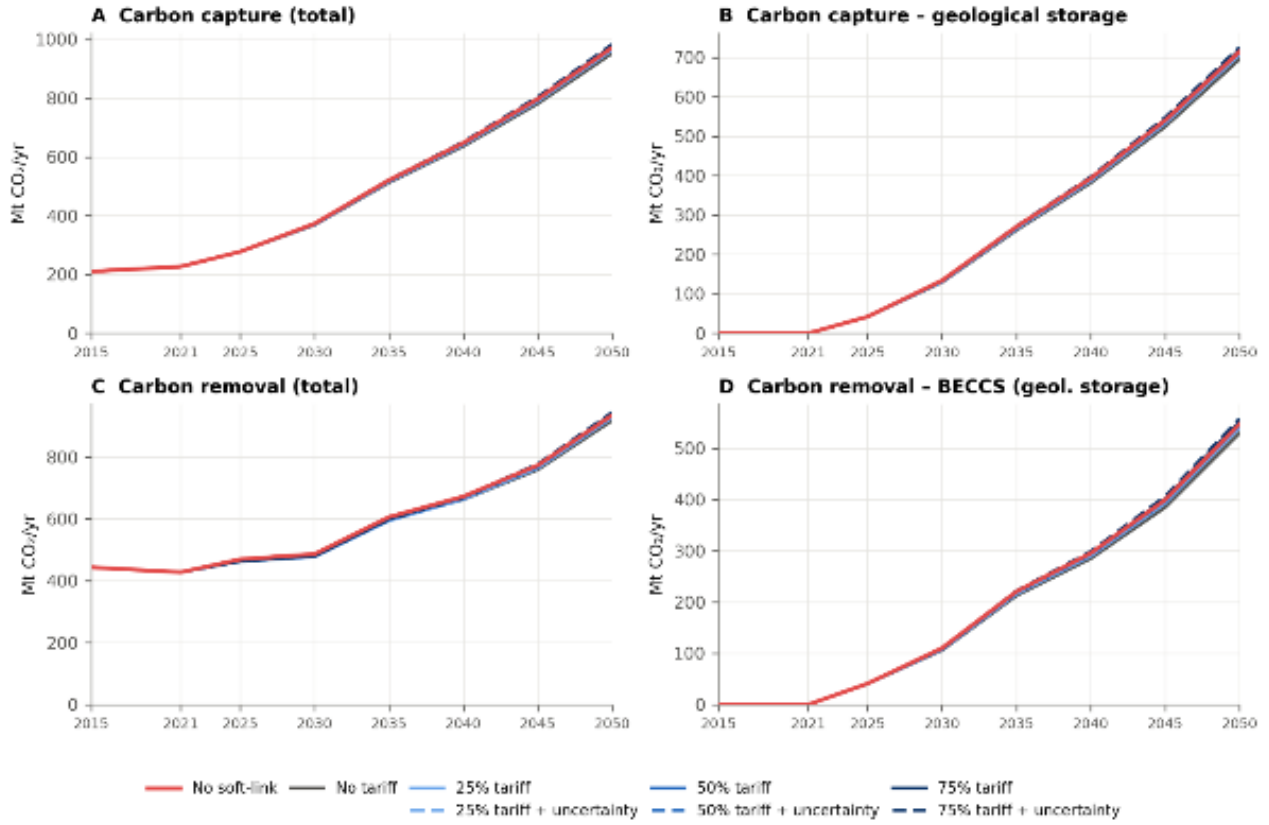

Figure 5.18. GCAM Europe – EU-27 Carbon Capture and Removal: Baseline vs. Soft-Link.
(A) Carbon capture (total), (B) carbon capture with geological storage, (C) carbon removal (total) and (D) carbon removal through geological storage of biogenic CO_2 (BECCS), in Mt CO_2/yr. Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

The scenario with price uncertainty had to be run with a different model calibration (affecting overall commodity trade) because it initially did not solve. Its transport-related results are consistent with the other scenarios (Figure A5.13): the BEV share reaches 43% in 2050, between the baseline soft-link (47%) and the 25% tariff scenario (40%), and transport emissions amount to 354 Mt CO_2. System-level outcomes, however, deviate strongly. Because these deviations are already visible in 2025, before the behavioural soft-link takes effect, they reflect the alternative calibration rather than behavioural effects, and we do not interpret system-level outcomes of this scenario.

Taken together, the GCAM Europe results show that the behavioural soft-link raises EV diffusion and lowers transport emissions throughout the modelling horizon, while disruptive events attenuate EV diffusion to or below the level of the run without soft-link, shifting the mitigation burden to other sectors such as carbon capture and removal, and energy production.

5.3.3 OMNIA

For OMNIA, we focus on three sets of model outcomes: the share of EVs in the car fleet, CO_2eq emissions by source (including captured CO_2), and passenger-car costs. All nine scenarios are compared for the three OMNIA macro-regions (EUE, EUM, EUW; country estimates based on the psychological experiment were aggregated for these regions) and the EU total over the modelling horizon 2019 to 2050.

Figure 5.19 shows the EV share in the car fleet. As in CLEWs-EU, the soft-link mainly changes the timing of EV uptake. With the baseline soft-link, the BEV share of the EU car fleet increases earlier than without soft-link (19% vs. 15% in 2030 and 35% vs. 17% in 2035) but levels off at 43% in 2050, whereas the run without soft-link rises steeply after 2035 and reaches 100% in all regions by 2050, a pattern that might be explained by BEVs being a relatively cheap decarbonization technology. High BEV diffusion is the logical result of climate targets without a constraint on diffusion. Under the baseline soft-link, the BEV share in 2050 ranges from 36% in EUE to 46% in EUM. Disruptive events have a strong effect in OMNIA. In 2050, EV tariffs of 25%, 50% and 75% reduce the BEV share to 26%, 19% and 13%, respectively, price uncertainty alone reduces it to 35%, and the combination of a 75% tariff and price uncertainty to 10%. With tariffs, the BEV share already falls below the run without soft-link in 2030. However, the model largely compensates for lower BEV adoption by shifting to plug-in hybrid and fuel-cell vehicles: the combined share of all alternative-fuel vehicles reaches 93 to 95% of the EU car fleet in 2050 in all soft-link scenarios (bottom row). Disruptive events therefore mainly change the technology mix rather than the final share of alternative-fuel vehicles.

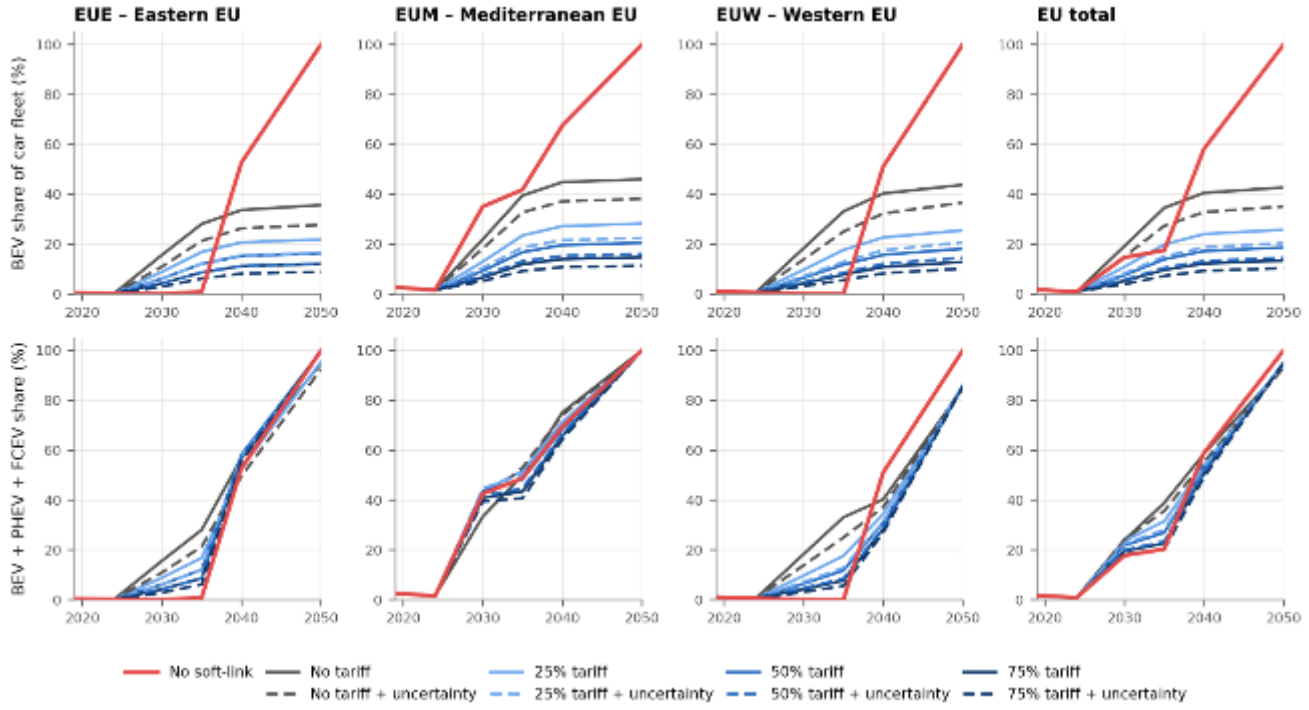

Figure 5.19. OMNIA – Share of EVs by Region: Baseline vs. Soft-Link.
Share of battery-electric vehicles (top) and of battery-electric, plug-in hybrid and fuel-cell vehicles (bottom) in the car fleet per OMNIA macro-region (EUE, EUM, EUW) and the EU total. Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

Figure 5.20 shows emissions by source. Total emissions decline to net zero in all scenarios and are virtually identical across the soft-link scenarios, as all runs are constrained by the same emission target. Differences emerge at the sector level. Transport emissions are lower with the baseline soft-link than without soft-link until 2035 but higher afterwards, as the run without soft-link almost fully decarbonises car transport by 2050. Disruptive events increase

residual transport emissions further, up to 142 Mt CO_2eq in 2050 in the 75% tariff and uncertainty scenario, with the largest increases in EUM and EUW. These residual emissions are compensated in the electricity sector, whose emissions become more negative with the severity of the disruptive event (from −194 Mt CO_2eq under the baseline soft-link to −246 Mt CO_2eq in the 75% tariff and uncertainty scenario in 2050), and by more captured CO_2. This mirrors the compensation through carbon capture and removal observed in CLEWs-EU and GCAM Europe.

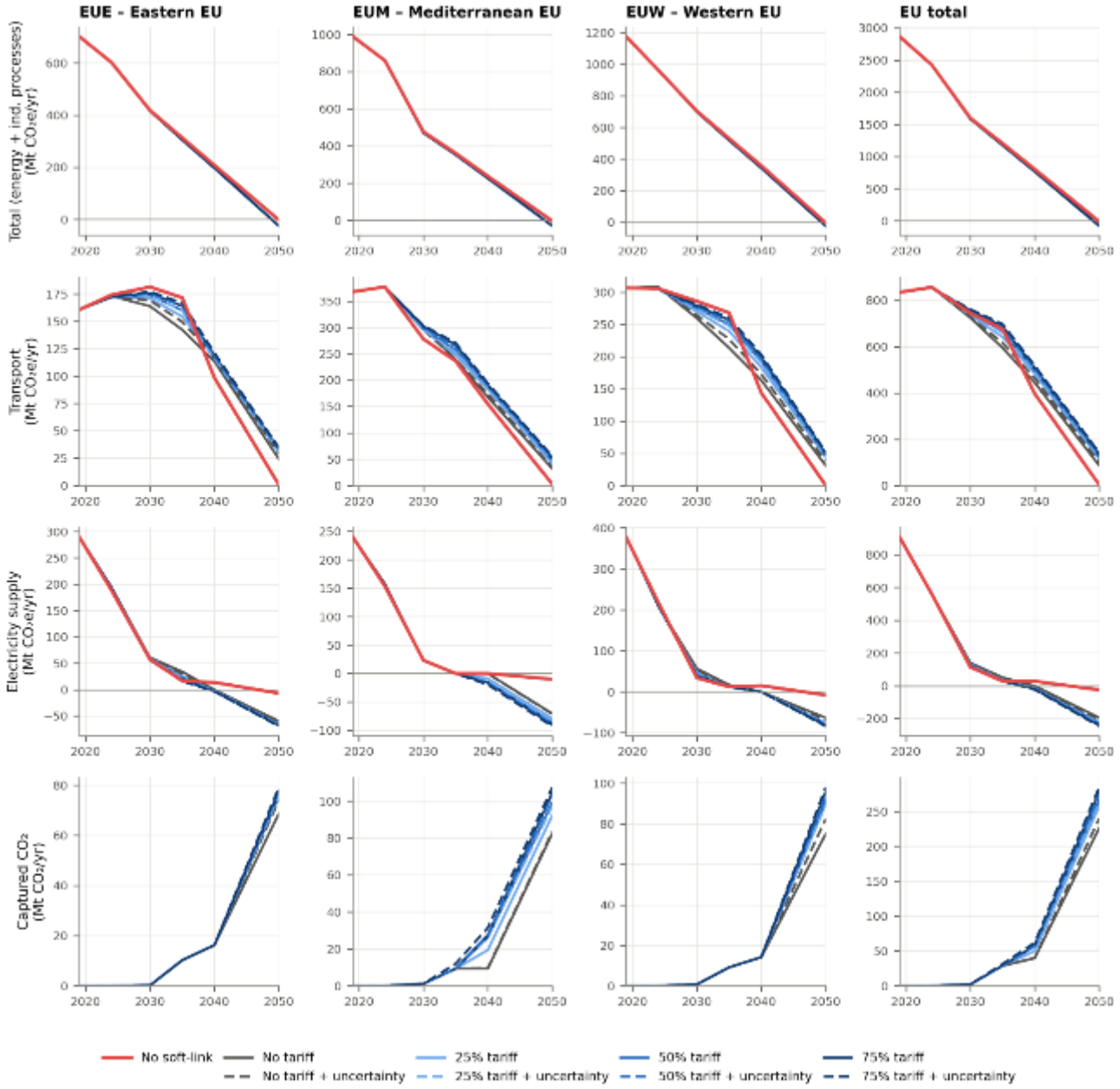

Figure 5.20. OMNIA – Emissions by Source: Baseline vs. Soft-Link.
CO_2eq emissions from energy and industrial processes (total), transport and electricity supply (Mt CO_2eq/yr), and captured CO_2 (Mt CO_2/yr) by macro-region and the EU total. Captured CO_2 is not reported for the run without soft-link. Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

Figure 5.21 shows the resulting differences in passenger-car costs relative to the run without soft-link. Under the baseline soft-link, the cost difference peaks in 2035, when EV adoption is brought forward, and remains positive in 2050 because more expensive low carbon EV alternatives need to be adopted to compensate for lower EV

diffusion. Disruptive events reduce this intermediate peak, as fewer EVs are adopted early, but increase costs considerably by 2050, reflecting the later shift towards plug-in hybrid and fuel-cell vehicles. The investment component dominates the total difference, whereas fixed operation and maintenance costs are smaller. In EUW, all soft-link scenarios show lower costs than the run without soft-link in 2040, when the latter adopts EVs at scale. Taken together, the OMNIA results highlight that the behavioural soft-link mainly changes the timing of EV adoption, while disruptive events strongly attenuate BEV diffusion and shift the burden to other vehicle technologies, the electricity sector and carbon capture, with higher costs at the end of the modelling horizon.

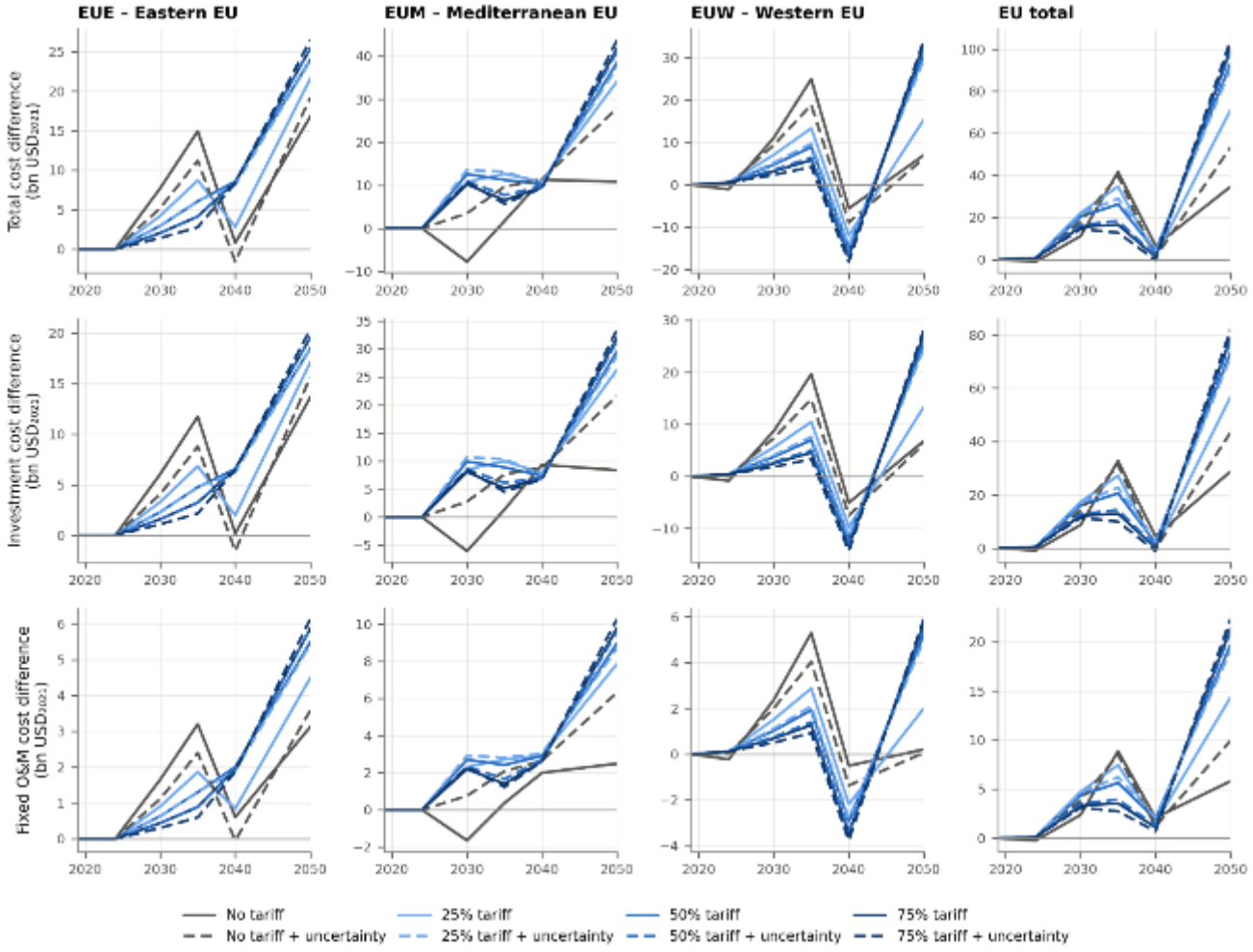

Figure 5.21. OMNIA – Passenger-Car Cost Differences: Soft-Link minus Baseline.
Difference in total, investment and fixed operation and maintenance (FOM) costs of passenger cars between each soft-link scenario and the DIAMOND baseline scenario without soft-link (bn USD_{2021}) per macro-region and the EU total. Grey = baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices. The zero line corresponds to the run without soft-link.

5.4 Discussion

5.4.1 ABM

By linking individual experimental decision data to scenarios of technological change and geopolitical and economic disruption, this study explores how disruption changes EV adoption decisions, for whom, and how policy can buffer or amplify those effects. Our two-wave discrete choice experiments show that the way disruption influences consumer decision-making can differ across countries: Willingness to adopt an EV fell in the U.S. and

Germany but rose in South Africa. The most consistent change in the choice models between the two waves is how respondents weight attributes. Purchase price became a stronger predictor once tariffs were included, indicating a higher sensitivity to price when respondents were told that part of the investment cost was a tariff. Furthermore, gasoline and electricity costs largely became insignificant predictors. A potential explanation for this effect is that that price volatility makes the operating-cost advantage of EVs harder to evaluate, and consumers do not consider it in their purchase decision.

These changes in choice attribute waves are also visible in the ABM-simulated policy effects. Subsidies became more effective during and after disruption in Germany and South Africa, though this effect was not visible in the U.S., where the change in subsidy effectiveness was smaller and fluctuated between positive and negative. This pattern might be explained by a) the subsidy being relatively higher in Germany and South Africa compared to the U.S., and b) the purchase price gaining more importance in the decision-making in Germany and South Africa under disruption. Carbon taxes, which work through fuel costs, became less effective in all three countries. The ICEV sales ban had the largest effect in South Africa, where adoption without it remained lowest. In all three countries, its anticipatory effect was greater in the scenarios with disruption. This suggests that policy announcements can give a signal in which direction personal mobility develops when prices and trade conditions are not, and that such announcements can influence adoption before implementation. Among the disruptions, EV tariffs had the largest negative effect on adoption, followed by electricity price fluctuations, while gasoline price fluctuations did not play a large role. The tariff result is consistent with Liu et al. (2026), who link tariffs to stagnation of the U.S. EV market. The effects of the various disruption scenarios running from 2027 to 2032 faded by the late 2030s, so within our ABM disruption delays diffusion rather than completely halting it. However, this depends on the assumption that the underlying preferences return to their pre-disruption form.

The results split by income group show that higher-income groups generally adopted more, but the pattern varied by country. Disruption widened the gap between the highest and lowest income quintiles in Germany and South Africa but narrowed it in the U.S., at least during the disruption period. In South Africa, car owners in the lowest income quintile among our survey respondents are more vulnerable to price shocks and fluctuations compared to higher income quintiles.

Several study limitations need to be considered in interpreting our study. First, we simulated responses to disruption by presenting respondents with a hypothetical scenario, which may not fully capture actual preference changes. We do, however, expect respondents to be familiar with the included disruptions, given that we grounded our scenarios in recent actual disruptions: tariffs and energy price fluctuations. Waves 1 and 2 were completed only days to two weeks apart, so consistency effects cannot be excluded. Second, Wave 2 presented tariffs and energy price shocks together as one scenario. The coefficients therefore describe joint disruption. Third, our online panel samples may not represent the wider populations, particularly in South Africa, where online, English-speaking respondents are likely to be more urban and young. The high EV enthusiasm there should be interpreted with this in mind. On the modelling side, agents' preferences are fixed within each scenario, so they do not learn from the disruption itself. EV prices follow an experience curve tied to global growth, and there is no endogenous response of national manufacturers. Finally, the model has not been validated against observed adoption data, so the trajectories should be read as exploratory scenarios rather than forecasts.

5.4.2 IAMs

Across the three IAMs, the baseline behavioural soft-link mainly changes the timing of EV adoption. Compared with the DIAMOND baseline scenario, it brings EV uptake forward but levels off in the later time steps. Without the soft-link, adoption is driven by cost optimisation under the net-zero target, which results in a late and steep uptake that overtakes the soft-link around 2040 to 2050 in CLEWs-EU and OMNIA, and even reaches 100% in

OMNIA by 2050. In GCAM-Europe the run without soft-link remains below the soft-link throughout the modelling horizon. Unconstrained IAM runs may therefore underestimate near-term adoption potential and overestimate how fast consumers follow a cost-optimal switch late in the modelling horizon.

Soft-linking also reduces inter-model divergence in projected penetration. Before coupling, the two cost-optimising energy system models project high penetration by 2050, while the recursive-dynamic logit-based choice mechanism of GCAM-Europe projects a substantially lower share of around 30%. Incorporating the behavioural module brings the three models' projections closer together, towards an empirically informed range of approximately 40–50% by 2050. This convergence suggests that explicit behavioural representation can moderate divergence associated with the models' underlying choice assumptions, rendering projected outcomes less dependent on the modelling framework.

Disruptive events shift these behavioural trajectories downwards. EV adoption decreases with the tariff level, price uncertainty reduces it further, and their combination has the strongest effect. Because all runs share the same emission target, total emissions differ only slightly. The differences instead appear in where and when emissions are mitigated: residual transport emissions are compensated by carbon removal and by the electricity sector, and investments may be shifted in time. Behavioural realism therefore matters less for whether a modelled net-zero target is met than for what it relies on, including carbon removal options whose feasibility is itself uncertain (Anderson et al., 2023). While carbon removal may be a cost-efficient way to compensate for lower EV diffusion in IAMs, its actual scalability is questionable.

The ABM and the IAM soft-link results mostly align: EV tariffs are the disruption with the strongest negative effect on adoption, fuel-cost signals lose relevance under price volatility, and adoption slows or plateaus well below full electrification unless an ICEV sales ban is implemented. The main difference lies in how the disruptive events are implemented. In the ABM, disruptions are active from 2027 to 2032 and their effects fade by the late 2030s. In the IAM soft-links, disruptions are implemented as a permanent change in costs and preferences and therefore attenuate adoption throughout the modelling horizon.

The approaches also differ in what they can show. The ABM captures heterogeneous agents, policy interactions and distributional effects, such as wider income gaps in adoption under disruption in Germany and South Africa, but it does not capture system-level feedback. The IAMs capture this feedback, including carbon removal, electricity supply and investments, but not actor heterogeneity.

5.5 Conclusions

This chapter showed how empirically grounded behavioural data can be integrated into IAMs and how disruptive events change the resulting pathways. Across CLEWs-EU, GCAM Europe and OMNIA, the behavioural soft-link mainly changes the timing and level of EV adoption, while EV tariffs and energy price uncertainty substantially attenuate it. Under binding net-zero targets, lower EV adoption is compensated elsewhere in the energy system.

This chapter demonstrates the importance of informing IAMs by theoretically grounded behavioural data rather than by cost optimisation alone. This extends to the representation of actor heterogeneity in IAMs, which would enable the investigation of group-specific estimates that the behavioural module could already provide, and time-varying preferences, as explored in the ABM. These adjustments would enable a more in-depth evaluation of policies, including targeted policies for specific subpopulations (e.g., low-income households).

Net-zero pathways that depend on rapid EV uptake may be behaviourally optimistic. Policymakers should therefore focus on early action that supports adoption, which reduces the reliance on costly carbon removal later. In addition, trade and industrial policies such as EV tariffs, as well as energy price shocks, can considerably slow EV adoption. In uncertain periods of disruption, measures that lower purchase prices appear more robust than

instruments that target vehicle operating costs, such as carbon taxes. Targeted support for lower-income households may be needed where disruption widens adoption gaps.

More psychological research is needed on how behavioural drivers such as temporal discounting, environmental attitudes and social norms evolve over time and context, and on how to extrapolate behavioural estimates to future contexts with, for instance, much higher EV diffusion. Because the behavioural module builds on the Campbell paradigm and a multi-level contextual structure, it can be transferred to other climate-relevant behaviours, with sustainable food consumption as a promising candidate (Poore & Nemecek, 2018; Willett et al., 2019). Psychology can also help assess the realism of policy scenarios themselves, as in our ongoing collaboration with Wei Peng's team at Princeton University on implementing policy support into GCAM USA. Realising this potential requires sustained interdisciplinary collaboration between behavioural scientists and integrated-assessment modellers but offers a concrete path towards models that better reflect how people make decisions.

5.6 References

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6 Conclusions

The four scenario studies presented in this report demonstrate the value of advancing and linking Integrated Assessment Models to better represent the technological, economic, behavioural and social dimensions of the low-carbon transition. Through the new modelling capabilities developed in DIAMOND and their application across multiple co-designed scenarios, the analysis provides a more realistic and policy-relevant understanding of how climate mitigation pathways can be achieved and what conditions determine their effectiveness, costs, and distributional impacts.

A common finding across the four studies is that achieving deep decarbonisation requires going beyond conventional technology-focused approaches. Circular economy measures, household heterogeneity, labour and financing constraints, and consumer behaviour all influence mitigation outcomes, technology uptake, and the distribution of transition costs and benefits. Models that overlook these dimensions risk underestimating implementation challenges.

The analysis highlights the importance of broadening the portfolio of mitigation actions. Circular economy measures can significantly reduce emissions from basic material sectors while lowering the overall costs of decarbonisation and generating wider resource efficiency benefits. At the same time, international cooperation is shown to be essential for maximising these gains, particularly though the inclusion of major producer countries and international supply chains.

Distributional considerations also emerge as critical determinants of the feasibility and effectiveness of climate policies. Income structures, labour market frictions, affordability constraints and heterogeneous consumer preferences all shape the effectiveness of climate policies. The results show that carbon pricing, while effective in driving emissions reductions, can impose disproportionate burdens on low-income households unless accompanied by well-designed revenue recycling and targeted support measures. Similarly, labour transition policies must address skills recognition and labour mobility, as well as support low-income households in accessing clean technologies such as heat pumps and electric vehicles.

Financing conditions and behavioural factors further influence the pace and composition of technology deployment. Access to affordable capital influences the pace and composition of investments in the energy system, while explicit representation of consumer preferences and social norms reveals lower rates of EV adoption than typically projected by conventional IAMs. These findings suggest that achieving climate targets may require more targeted policy interventions, including investment support, subsidies, and communication programmes that reduce affordability barriers and increase public acceptance and uptake of low-carbon technologies.

Overall, the modelling advances developed in DIAMOND strengthen the capacity of IAMs to assess not only whether climate targets can be achieved, but also how they can be achieved in ways that are economically efficient, socially equitable, politically feasible and resilient to future uncertainties. By incorporating dimensions often overlooked in conventional assessments, the project provides a stronger analytical foundation for designing effective, equitable and implementable mitigation strategies, supporting climate and sustainability policymaking at both European and global levels.

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ANNEX. Additional figures for Chapter 5

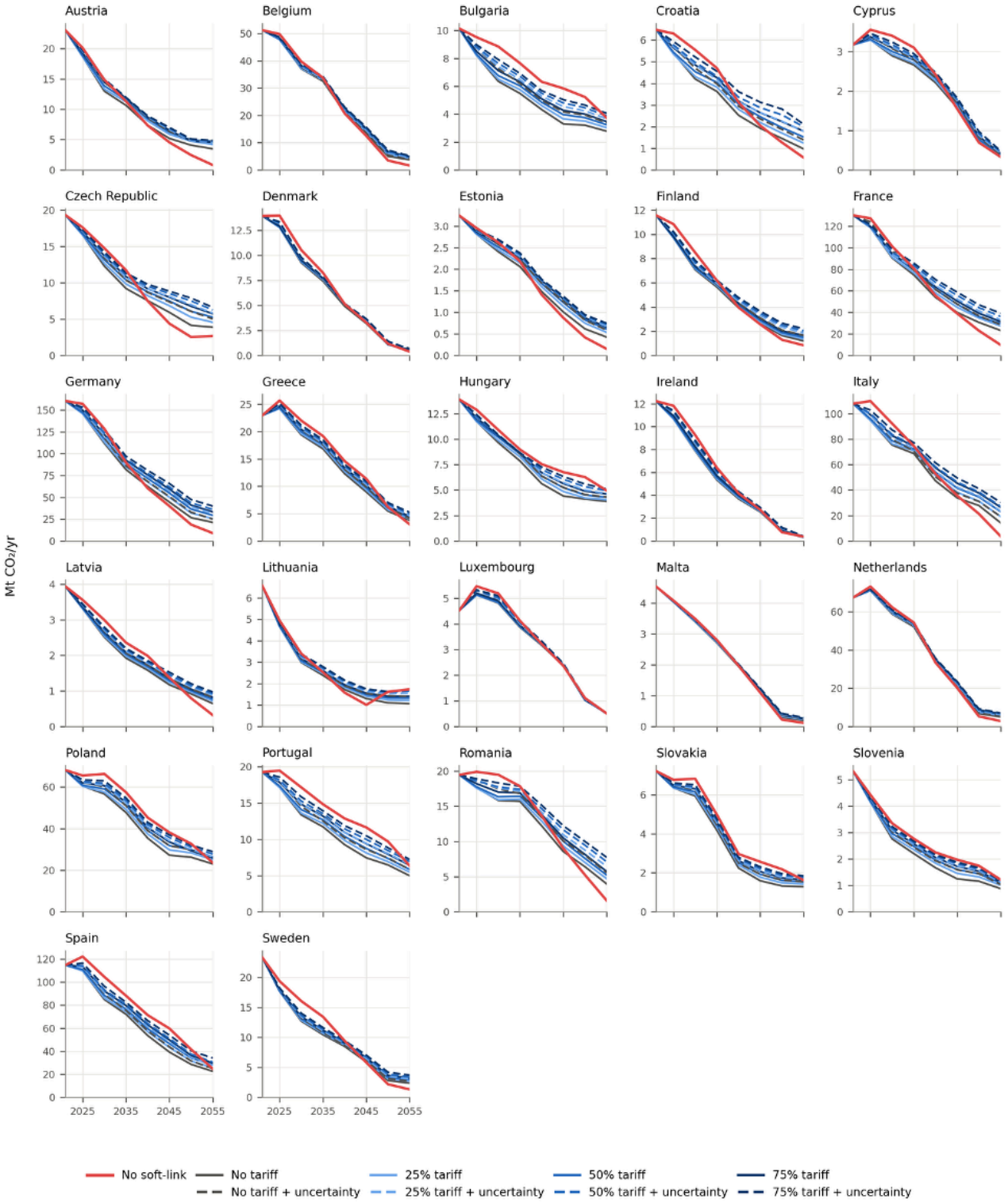

Figure A5.1. CLEWs-EU – Transport CO_2 Emissions by Country (Mt CO_2/yr; country-specific y-axes). Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

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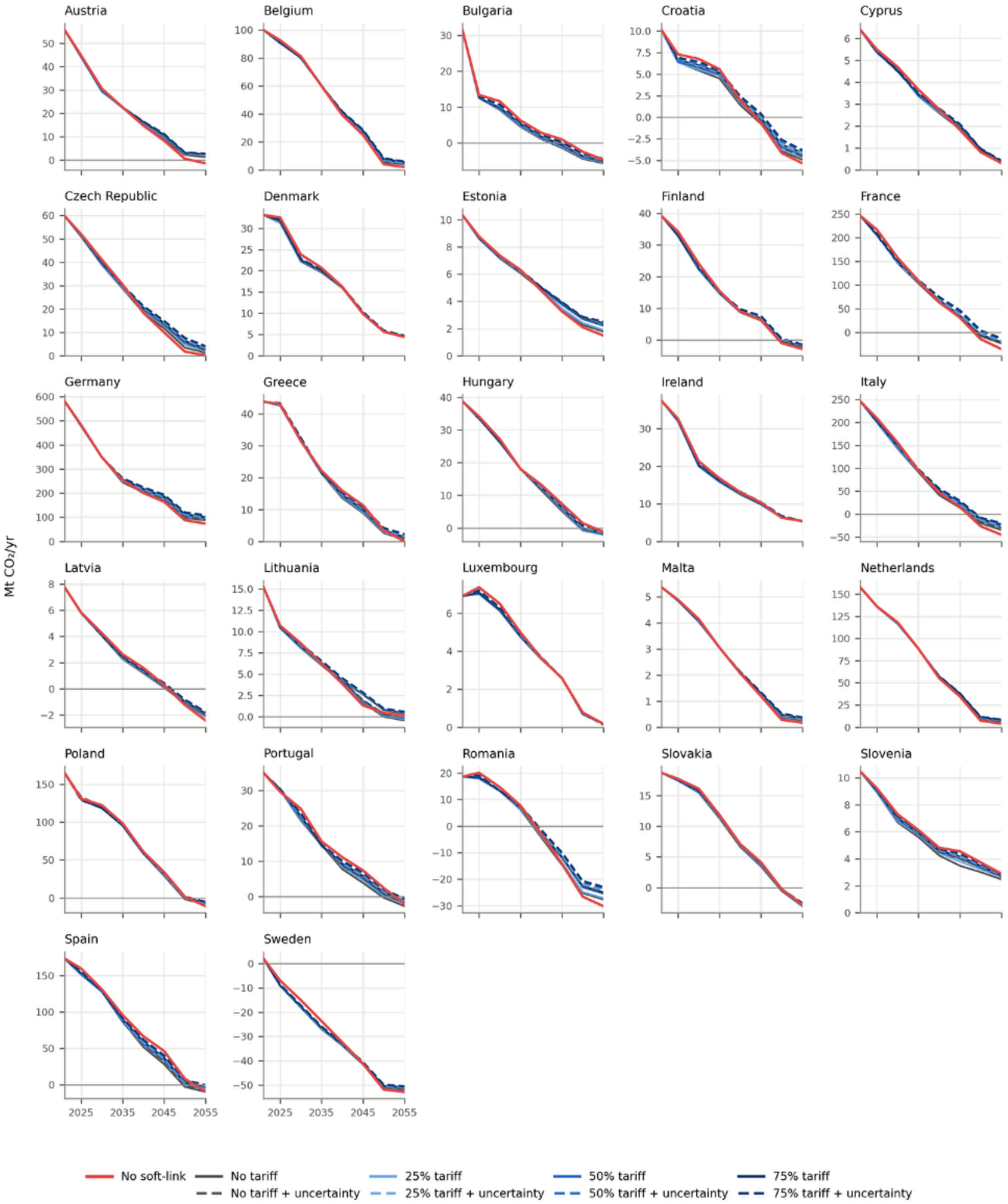

Figure A5.2. CLEWs-EU – Total CO_2 Emissions (Energy and AFOLU) by Country (Mt CO_2/yr; country-specific y-axes). Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

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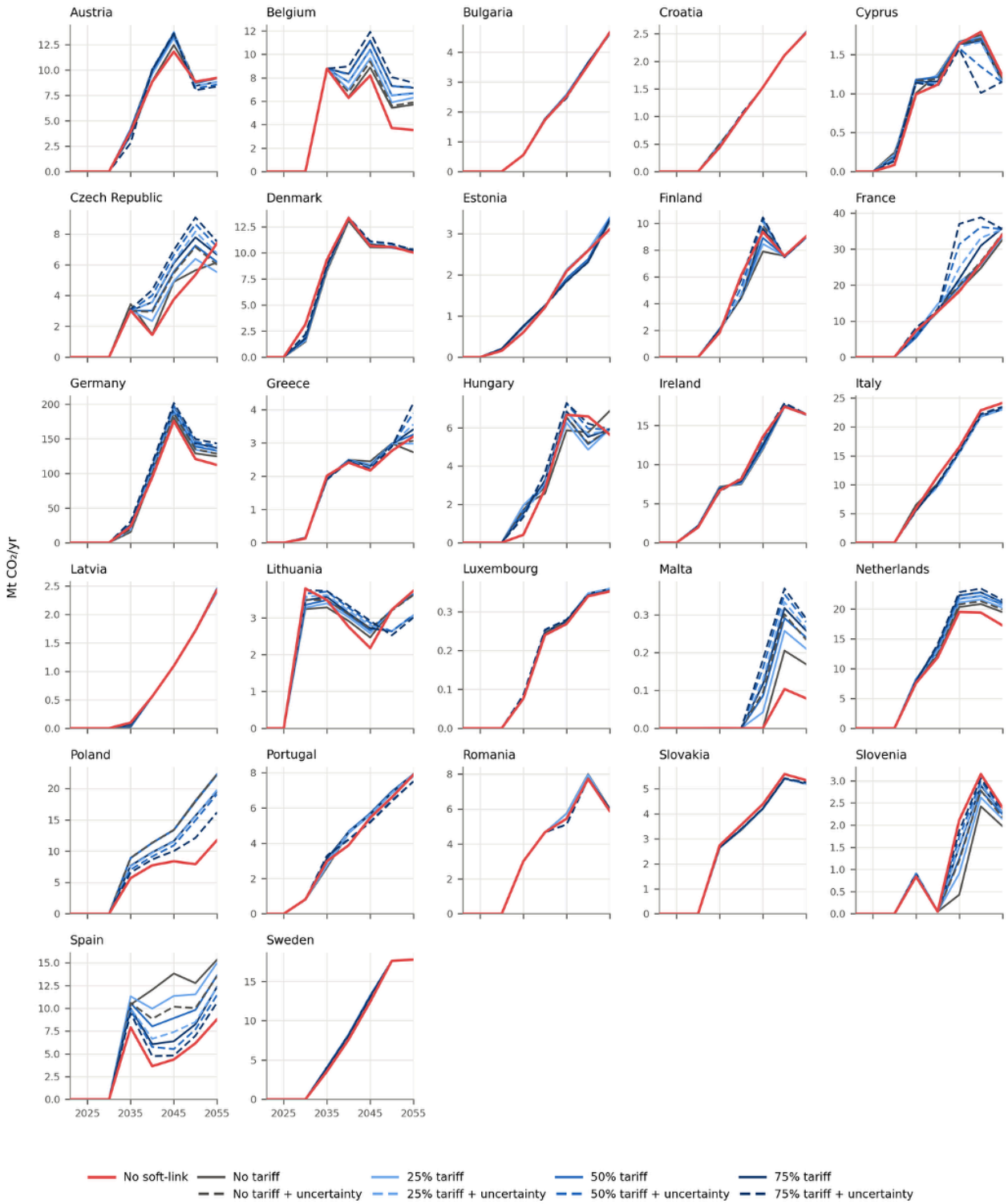

Figure A5.3. CLEWs-EU – Carbon Capture (CCS and Direct Air Capture) by Country (Mt CO_2/yr; country-specific y-axes). Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

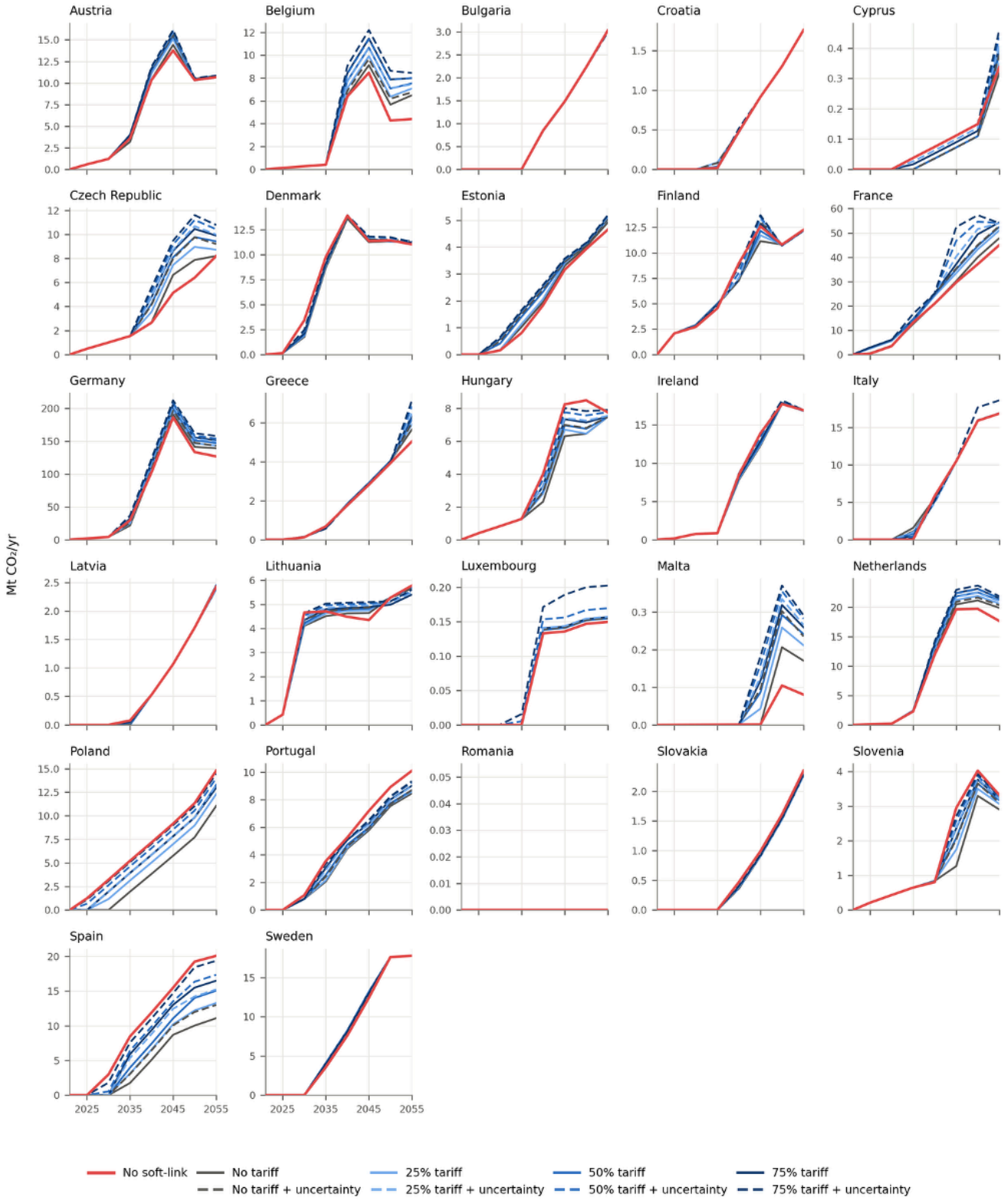

Figure A5.4. CLEWs-EU – Carbon Removal (BECCS, Direct Air Capture and Afforestation) by Country (Mt CO_2/yr; country-specific y-axes). Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

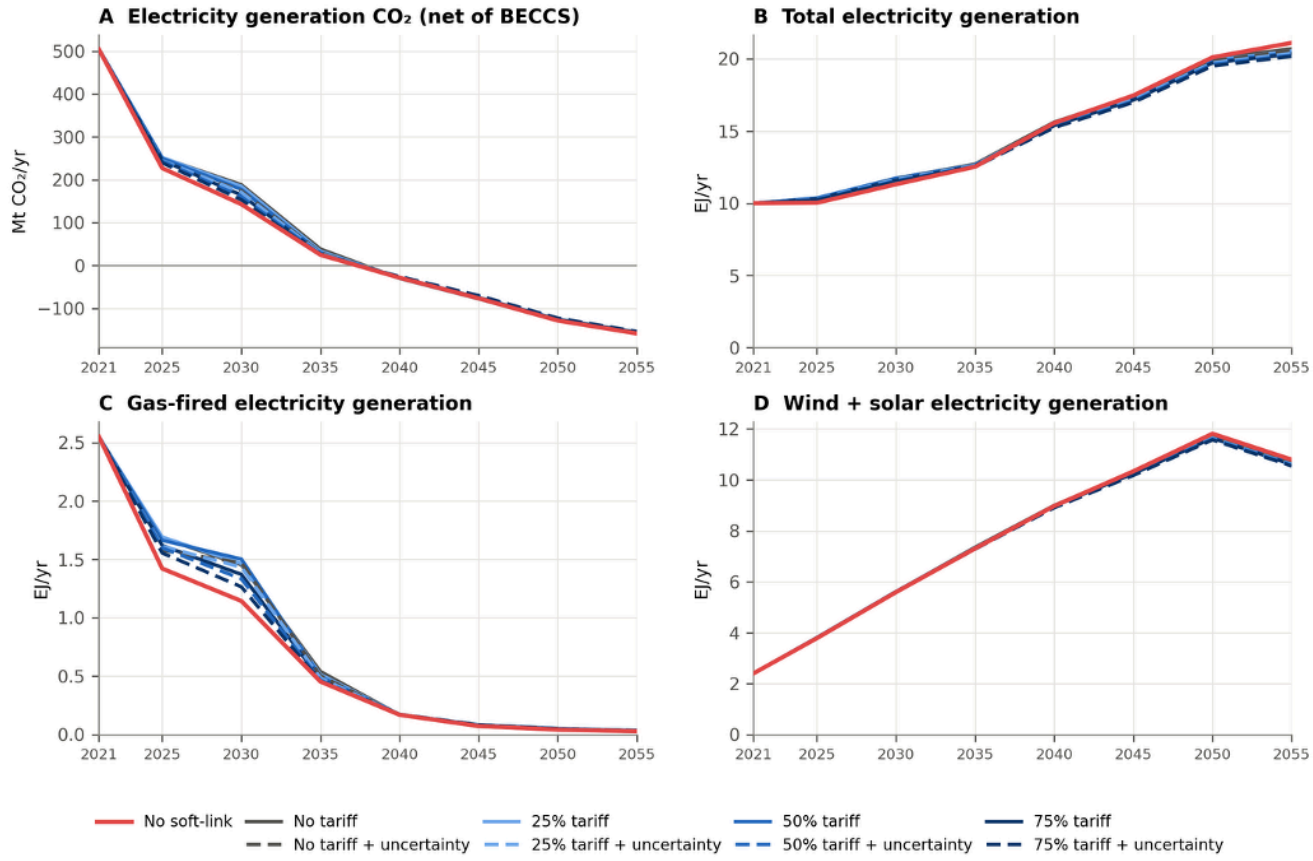

Figure A5.5. CLEWs-EU – EU-27 Electricity Supply. (A) CO_2 emissions from electricity generation (net of BECCS), (B) total electricity generation, (C) gas-fired generation and (D) wind and solar generation. Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

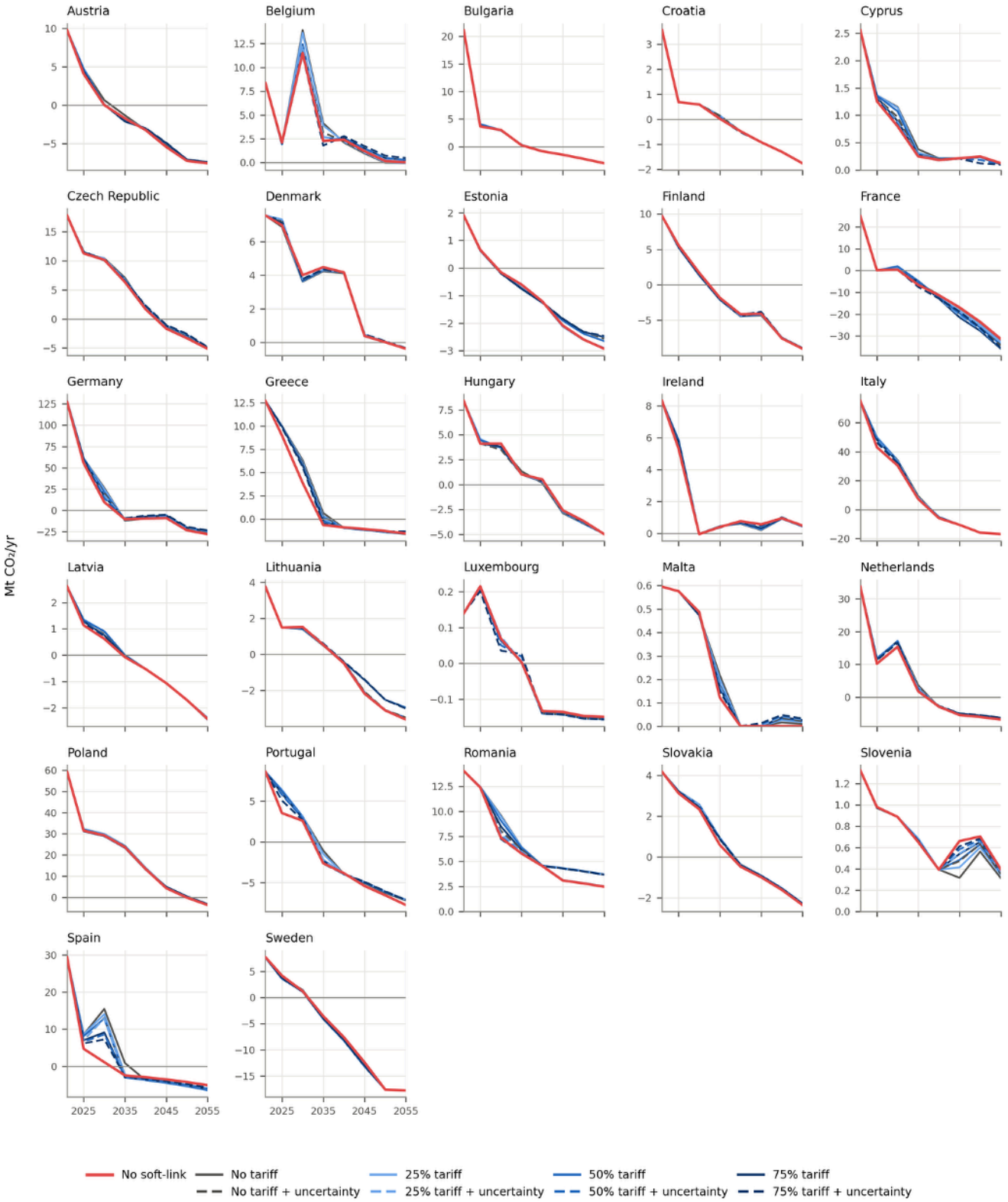

Figure A5.6. CLEWs-EU – CO_2 Emissions from Electricity Generation by Country (Mt CO_2/yr; country-specific y-axes). Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

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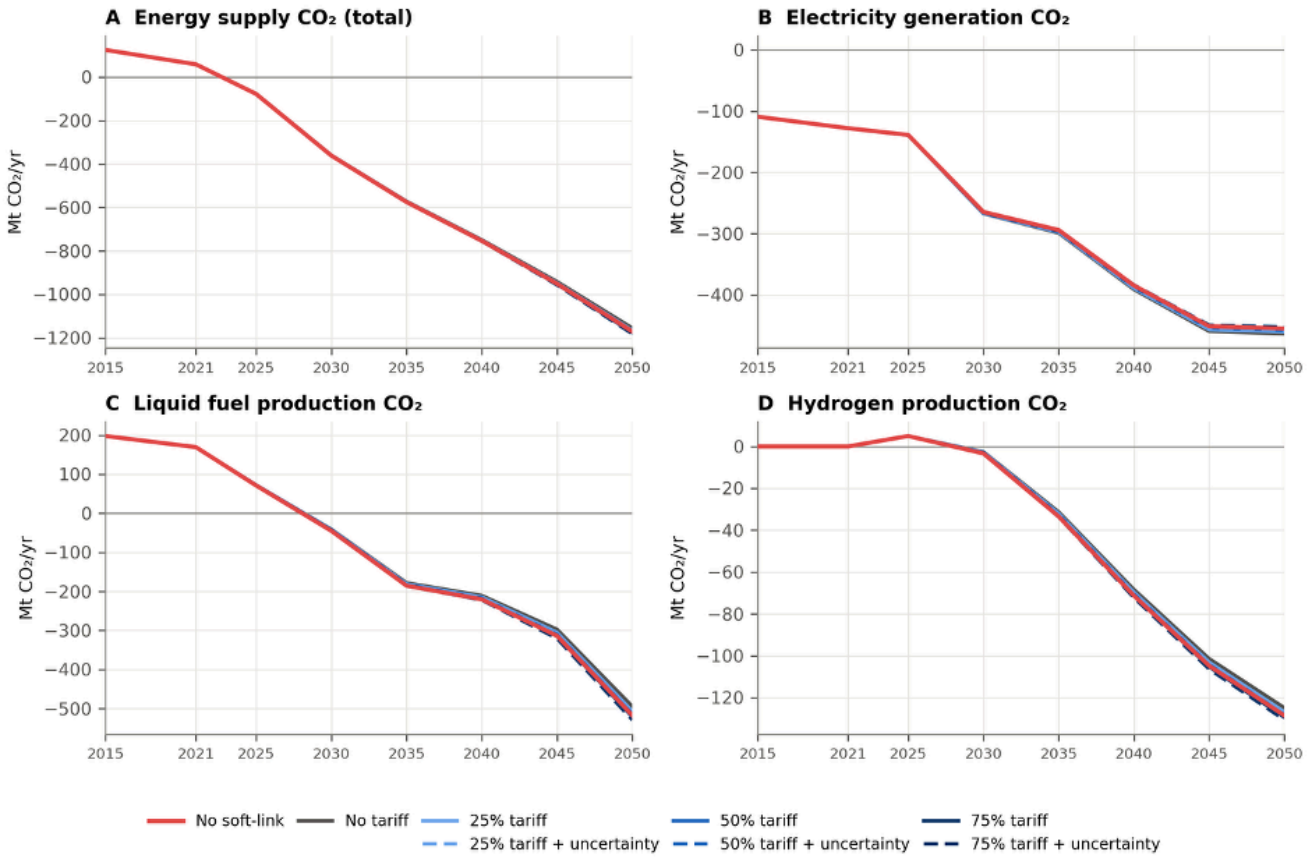

Figure A5.7. GCAM Europe – EU-27 CO_2 Emissions from Energy Supply (net of BECCS). (A) Total energy supply, (B) electricity, (C) liquid fuels and (D) hydrogen, in Mt CO_2/yr. Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

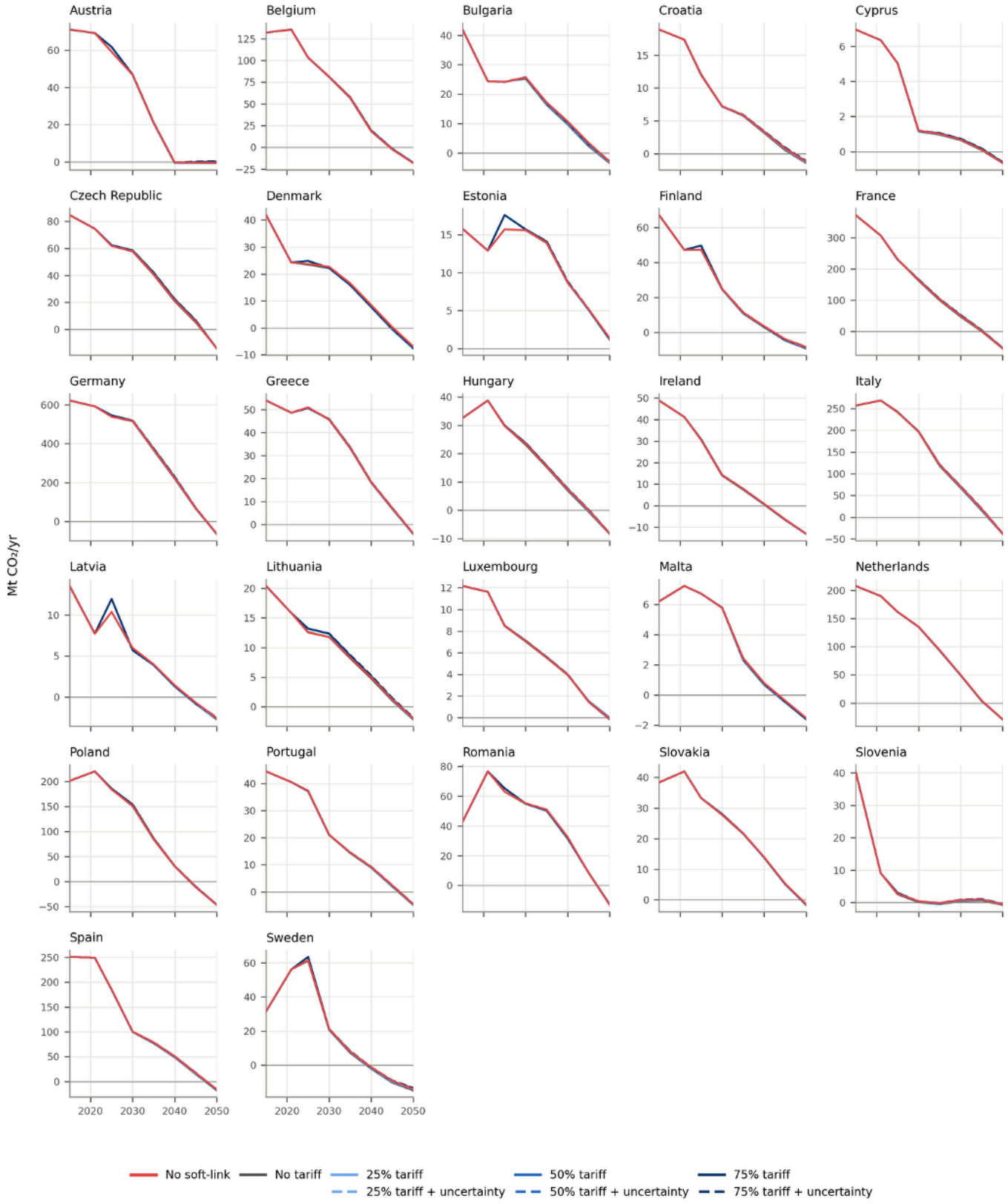

Figure A5.8. GCAM Europe – Total System CO_2 Emissions by Country (Mt CO_2/yr; country-specific y-axes). Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

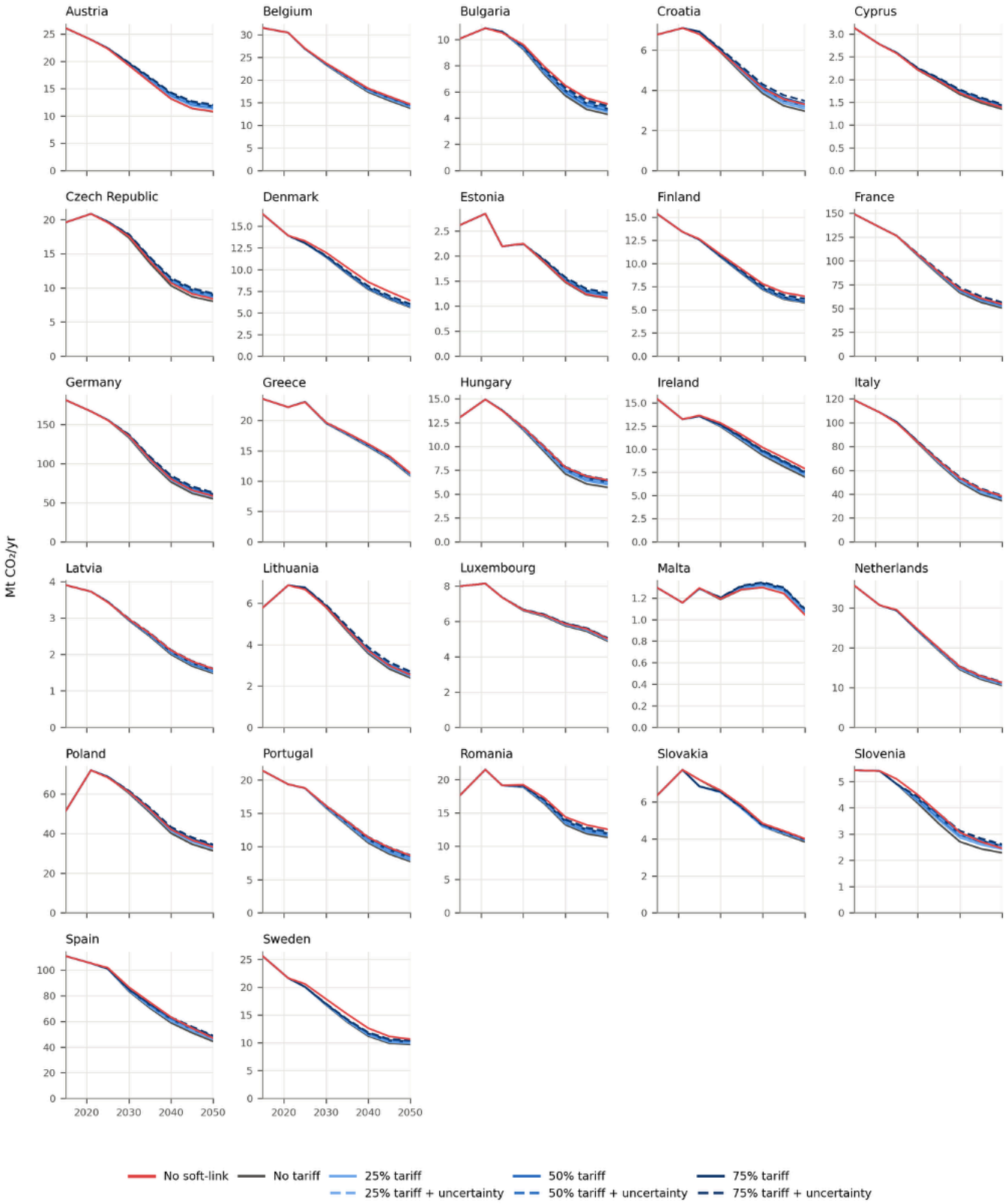

Figure A5.9. GCAM Europe – Transport CO_2 Emissions by Country (Mt CO_2/yr; country-specific y-axes). Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

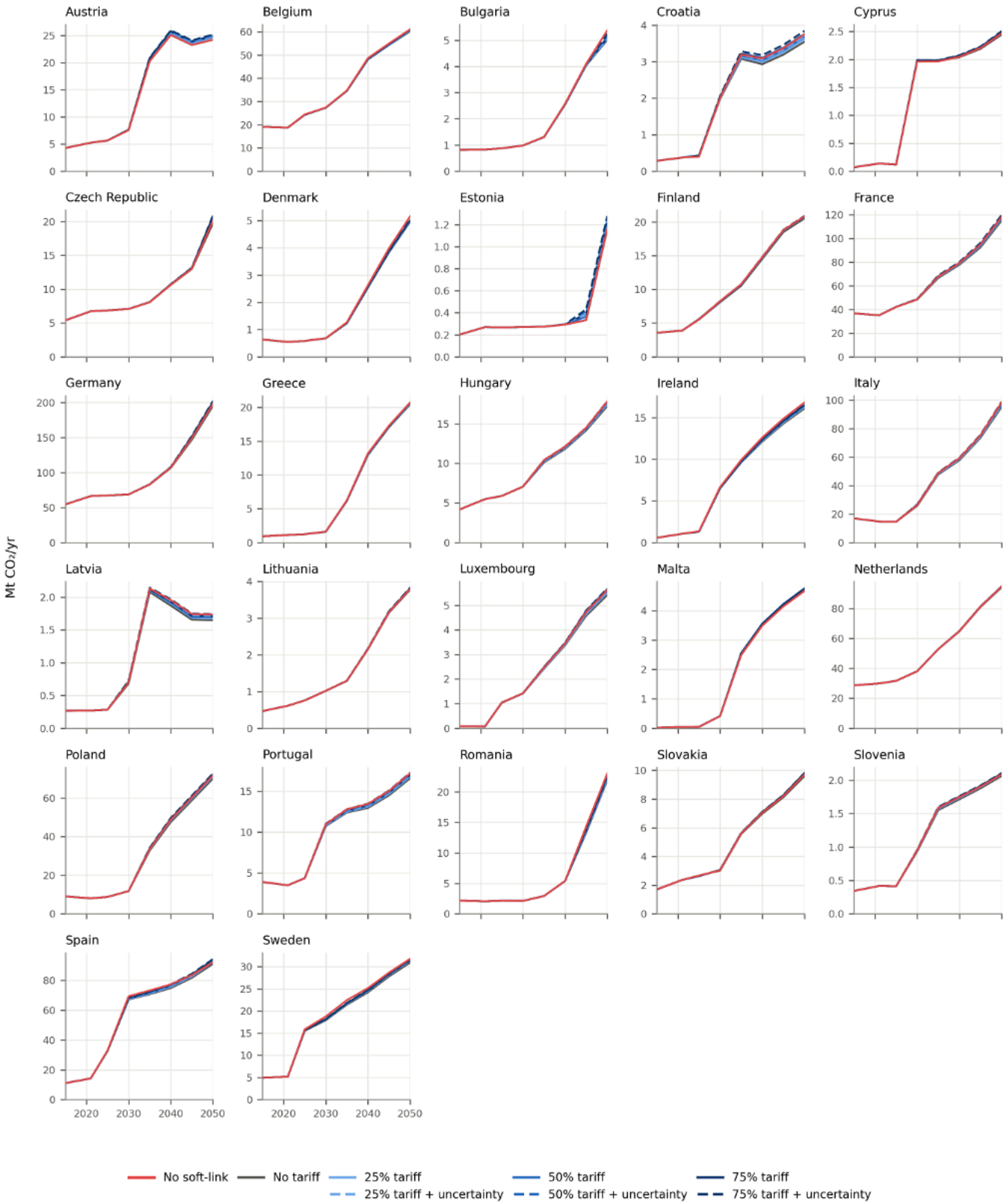

Figure A5.10. GCAM Europe – Carbon Capture by Country (Mt CO_2/yr; country-specific y-axes). Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

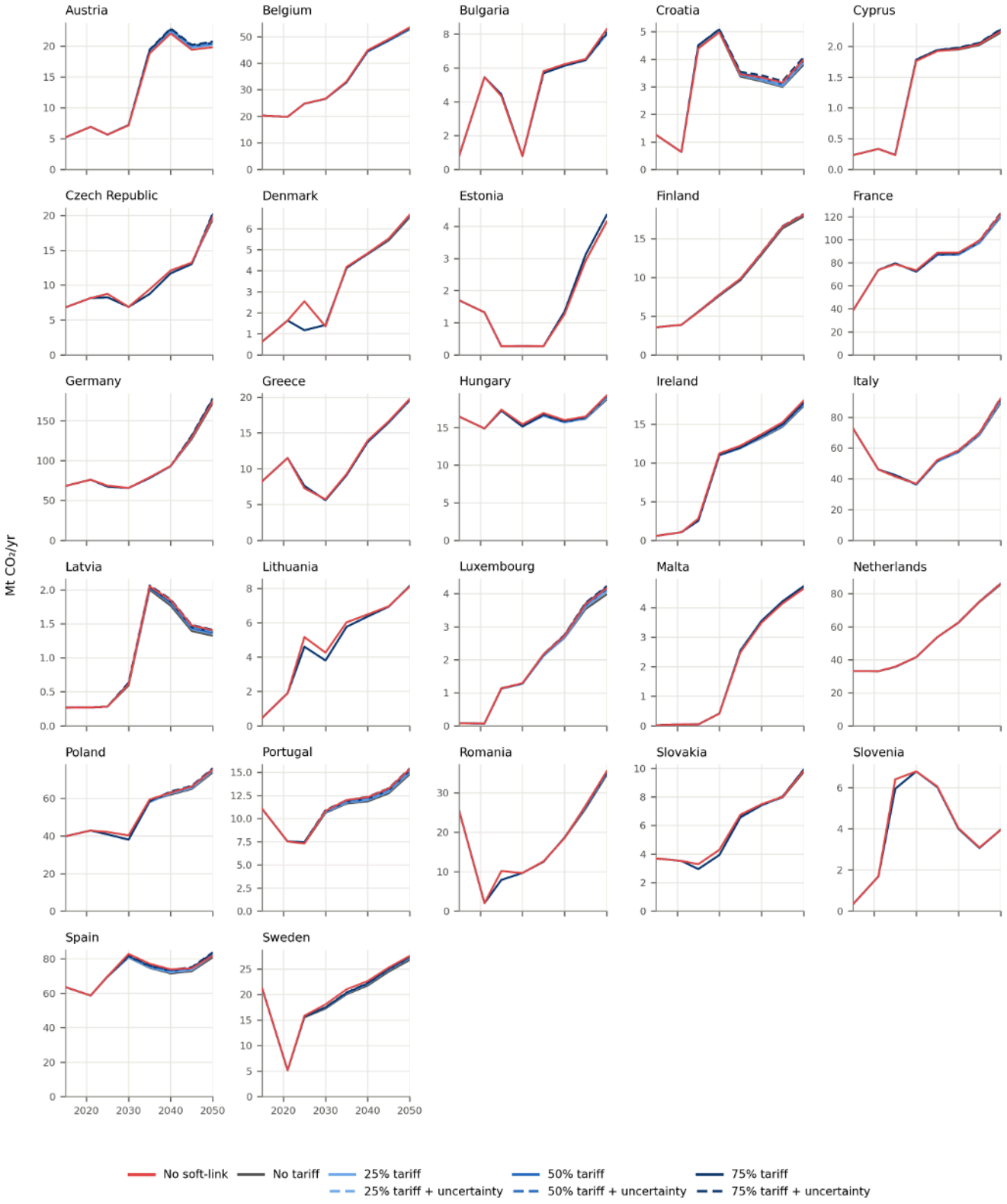

Figure A5.11. GCAM Europe – Carbon Removal by Country (Mt CO_2/yr; country-specific y-axes). Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

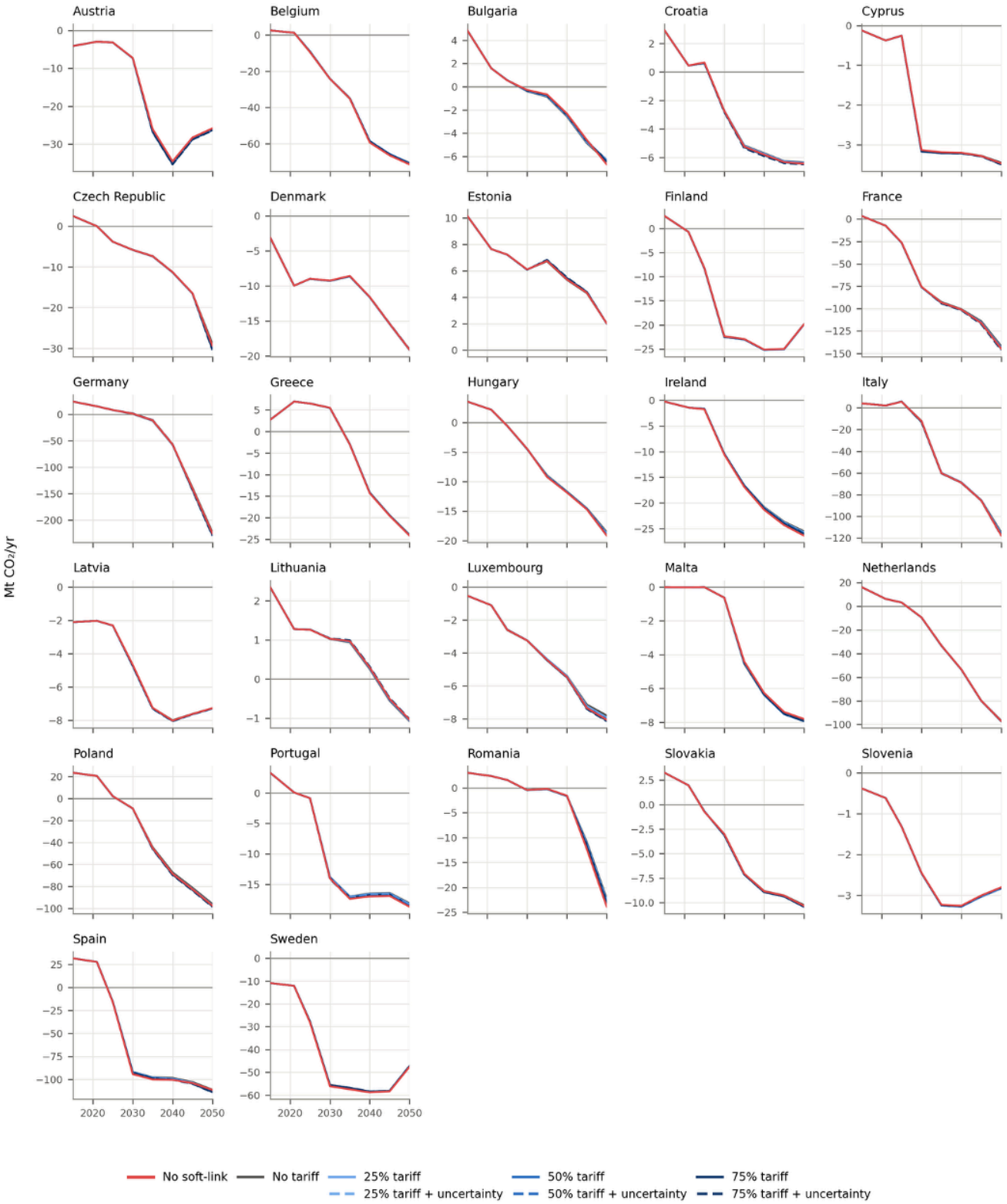

Figure A5.12. GCAM Europe – CO_2 Emissions from Energy Supply by Country (Mt CO_2/yr; country-specific y-axes). Red = DIAMOND baseline scenario without soft-link; grey = DIAMOND baseline including the baseline behavioural soft-link (no disruptive event); blue lines = disruptive-event soft-links with 25% (light), 50% (medium) and 75% (dark) EV tariffs; dashed lines = additional uncertainty in fuel and electricity prices.

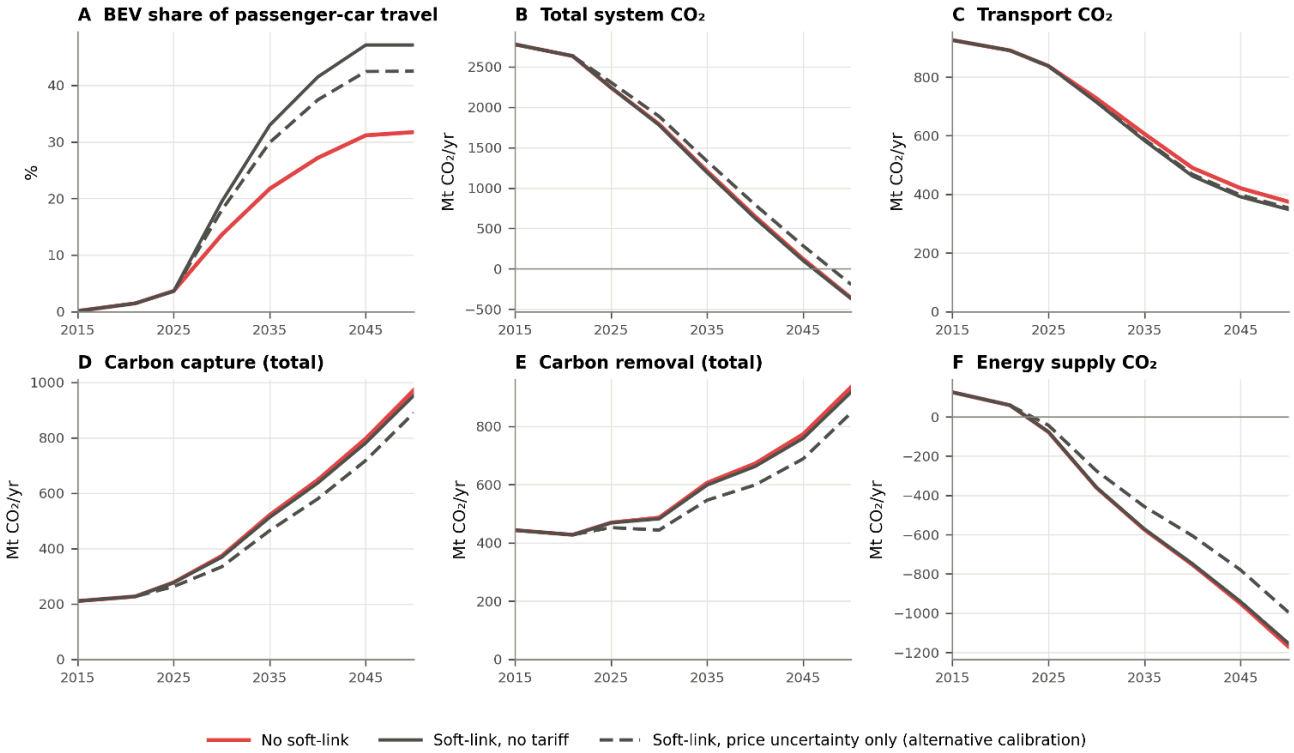

Figure A5.13. GCAM Europe – EU-27 Results of the Price-Uncertainty-Only Scenario. The scenario was run with an alternative calibration (see footnote in Section 5.3.2); its system-level outcomes are therefore not directly comparable with the other scenarios. Red = DIAMOND baseline scenario without soft-link; solid grey = baseline soft-link; dashed grey = soft-link with price uncertainty only.