Grant agreement no. 730403

INNOPATHS

Innovation pathways, strategies and policies for the Low-Carbon Transition in Europe

H2020-SC5-2016-2017/H2020-SC5-2016-OneStageB

D4.2 Report on social and distributional implications and ways of alleviating adverse social effects

Work Package: 4

Due date of deliverable: Month 47, October 31 2020

Actual submission date: November 24, 2020

Start date of project: December, 01 2016 Duration: 56 months

Lead beneficiary for this deliverable: *E3-Modelling (E3M)*

Contributors: UCL, SPRU

Authors: Panagiotis Fragkos, Leonidas Paroussos, Zoi Vrontisi, Kostas Fragkiadakis, Ioannis Charalampidis (E3M), Vincenzo De Lipsis (UCL), Benjamin Sovacool (SPRU), Francesco Vona (SPO)

Internal reviewers: Paul Drummond (UCL)

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Project co-funded by the European Commission within the H2020 Programme (2014-2020)		
Dissemination Level		
PU	Public	x

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Disclaimer

The content of this deliverable does not reflect the official opinion of the European Union. Responsibility for the information and views expressed herein lies entirely with the author(s).

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Table of Contents

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Version log

Version	Date	Released by	Nature of Change
1	20/07/2020	Panagiotis Fragkos	First outline
2	25/08/2020	Panagiotis Fragkos	Updated structure
3	05/09/2020	Francesco Vona	Provision of study
4	06/09/2020	Vincenzo De Lipsis	Provision of study
5	02/10/2020	Panagiotis Fragkos	Provision and integration of studies
6	30/10/2020	Panagiotis Fragkos	Final study updates
7	15/11/2020	Panagiotis Fragkos	Version released for internal review
8	20/11/2020	Paul Drummond	Study review
9	22/11/2020	Panagiotis Fragkos	Version sent to partners for final update
10	24/11/2020	Panagiotis Fragkos	Final version submitted

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Definition and acronyms

Acronyms	Definitions
AEEI	Autonomous Energy Efficiency Improvements
ARRA	American Recovery and Reinvestment Act
CGE	Computable General Equilibrium
CES	Constant Elasticity of Substitution
CO2	Carbon dioxide
EC	European Commission
EGD	European Green Deal
EITE	Energy Intensive Trade Exposed industries
EU	European Union
EV	Electric Vehicle
e-fuels	Synthetic Fuels
GDP	Gross Domestic Product
GHG	Greenhouse gas
H2	Hydrogen
IAM	Integrated Assessment Model
ICE	Internal Combustion Engine
NDC	Nationally Determined Contribution
RES	Renewable Energy Sources
R&I	Research and innovation
SSP	Shared Socioeconomic Pathways
TFP	Total Factor Productivity
toe	Tonnes of oil equivalent
vkm	Vehicle kilometre

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Executive Summary

A. Overview of the research and motivation

The INNOPATHS project aims to provide a fully-fledged assessment of the social and distributional implications of ambitious European climate policies and ways of alleviating adverse social effects. In this context, the deliverable D4.2 aims to provide a comprehensive analysis of the effects of EU climate policies on the incomes, activity and consumption patterns of firms and households and a detailed evaluation of potential policy instruments to minimize the adverse effects on vulnerable low-income households and trade-exposed industries. This deliverable presents a series of research papers which provide insights on the social and distributional impacts of energy and climate policies towards the transformation of the European Union (EU) economy and society in line with the EU Green Deal and the long-term strategy for climate neutrality by mid-century. The analysis considers both medium- and long-term developments that need to take place to pave the way towards the EU economy restructuring. In addition, the analysis explores the socio-economic impacts and of past and current climate policies and evaluates the historical preferences of various income classes across EU countries. Finally, the research papers present new methodological improvements developed in task 4.2, both related to advanced econometric techniques as well as beyond the state-of-the-art modelling enhancements in the macro-economic GEM-E3-FIT model which allow an improved representation of the social and distributional impacts of climate policies across income classes in EU countries.

Within the research activities of this task, the participating teams developed new modelling capabilities in the General Equilibrium framework of GEM-E3-FIT in order to improve the representation of social and distributional impacts of policies in the income and consumption patterns of various income classes. This was complemented with a detailed review of the state-of-the-art in modelling frameworks depicting distributional impacts for interdisciplinary policy analysis, focusing mostly on macro-economic general equilibrium models. In addition, advanced econometric and statistical methods are used by University College London (UCL) to estimate different time preferences across income classes and countries. As the COVID-19 pandemic has had, and is having, tremendous impacts on European economies and society, Sciences-PO (SPO) assessed the distributional impacts of a post-pandemic green fiscal stimulus, focusing especially on skills, employment and wages of low-skilled manual workers.

The methodological advancements and model enhancements allowed the teams to delve into key research questions related to the social and distributional impacts of the transition to a low-carbon and climate-neutral economy by mid-century. The focus of the research activities lies on the following dimensions:

- **Beyond the energy system: modelling frameworks depicting distributional impacts for interdisciplinary policy analysis.** Since the signing of the 2030 Agenda for Sustainable Development by the United Nations and the Yellow vest movement, it is clear that distributional impacts of climate policies should be carefully considered to ensure sustainable and equitable economic growth compatible with the Paris Agreement goals. To

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

this end, the design of environmental and energy policies should be accompanied by an interdisciplinary analysis that includes potential effects on distinct groups of society (defined by income, age or location), regions and sectors. This study synthesizes common energy-economy modelling frameworks used to assess technical, socio-economic and environmental aspects with policy analysis and their recent progress to illustrate social and distributional impacts. Furthermore, we highlight the main indicators produced by each modelling method and present a critical review pointing to gaps and limitations in evaluating social impacts of climate policies that could be addressed by future research.

- **Exploring the differences in time preferences across income classes and countries.** In this research study, UCL researchers provide direct statistical evidence of existing differences in time preference across income classes and countries by estimating and testing an Euler equation for consumption on time series data for six European countries and five income quantiles. Using advanced econometric techniques, the research study rejects the hypothesis of homogeneous time preference across countries, whereas heterogeneity across income classes is confirmed to different degrees depending on the country, but with time preference being lowest for the last two quantiles of the income distribution.

- **Examining distributional effects of a post-pandemic green fiscal stimulus**. Supporters of green fiscal stimulus as a response to aid the recovery from the Covid-19 pandemic commonly argue that green stimuli would boost GDP, create jobs and help redirect economic systems towards climate neutrality. In this research study, SPO researchers provide new evidence on the distributional effects of green fiscal stimulus and show that skill distance and other barriers could limit a transition of unskilled labour displaced by automation and the Covid-19 crisis to green-manual jobs that are the main employment class beneficiaries of a green fiscal stimulus, according to the paper described above. Their ex-post assessment of the green component of the American Recovery and Reinvestment Act of 2009 suggests that training programs facilitate job-to-job transitions induced by a green stimulus, with areas equipped with green training facilities gaining the most in terms of employment and wages for green-manual jobs after a green fiscal stimulus.

- **Assessing the social and distributional impacts of ambitious climate policies in Europe with GEM-E3-FIT.** Ambitious climate policies may lead to regressive distributional impacts disproportionately affecting low-income groups, as the imposition of additional taxes on energy products may increase the risk of energy poverty. In the current study, the state-of-the-art general equilibrium model GEM-E3-FIT is expanded to represent ten income classes in EU Member States, by differentiating their income sources, savings and consumption characteristics. The improved modelling capabilities are used to

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

quantify the distributional impacts of the EU Green Deal targets, in particular exploring their effects on labour income and energy-related expenditure by income class. The analysis shows that the transition to climate neutrality may increase modestly the inequality across income classes, with low-income households facing most negative effects. However, using carbon revenues as lump-sum transfers to households and to reduce social security contributions has clear benefits through increasing total employment, while significantly reducing the inequality and energy poverty from current levels across income classes in European countries.

- **Reducing the decarbonisation cost burden to EU industrial sectors**. The issues of industrial competitiveness and carbon leakage are key topics of the climate policy debate, especially in the EU. The imposition of carbon pricing without anti-carbon leakage measures impacts negatively the competitiveness of energy-intensive and trade-exposed industries inducing their relocation to countries without ambitious climate policies. Unilateral climate policy cannot directly impose carbon prices on foreign sources, but it can complement domestic emissions pricing with border carbon adjustment to reduce leakage and increase global cost-effectiveness of the mitigation effort. In the current study, we use an enhanced version of the multi-sectoral GEM-E3-FIT model to assess the risk of carbon leakage when the EU implements ambitious climate policies to achieve the EU Green Deal targets. Without preventative measures, most carbon leakage would flow to China, India and Russia, while the higher relocation to non-abating countries is projected for the metals and chemicals industries. The analysis shows that border carbon adjustment can effectively reduce carbon leakage and the adverse impacts on European energy-intensive industrial production, by shifting the economic burden of emission reduction to non-abating countries through implicit changes in product prices.

The following table presents the list of the research papers included in this Deliverable. Research paper P1 has been already published in a scientific journal[1], while research studies P2 and P3 have been submitted in scientific journals and are currently in the peer review process. The other two research studies included in this deliverable will be submitted for review in scientific journals, after the submission of the deliverable.

List of research papers under Deliverable D4.1

Author	Paper acronym	Paper title
E3M	P1	Beyond the energy system: modelling frameworks depicting distributional impacts for interdisciplinary policy analysis
UCL	P2	Is time preference different across incomes and countries?

[1] *Reference*

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

SPO	P3	Distributional effects of a post-pandemic green fiscal stimulus: skills, employment and wage of low-skilled manual workers
E3M, SPRU	P4	Assessing the social and distributional impacts of ambitious climate policies in Europe with GEM-E3-FIT
E3M	P5	Reducing the decarbonisation cost burden to EU industrial sectors

The thematic areas covered under the present deliverable are in line with the task requirements. In the following, we present the envisaged key thematic areas included in task requirements and how they are addressed by the five studies/ research papers.

Addressing Task requirements in the research papers

	Partner	Research paper
Review and assessment of distributional impacts of climate policies and ways of alleviating adverse social effects	E3M	#P1
UCL will perform an econometric estimation of the discount factors across income classes in EU countries taking into account budget constraints, intertemporal time and risk preferences.	UCL	#P2
We will quantify the impact of funding scarcity on income classes in EU Member-States, as well as on industrial sectors, and the likely adverse effects	E3M	# P4, P5
E3M will use the enhanced version of GEM-E3 with representation of multiple income classes to capture heterogeneous risk-averse behaviours. The model will simulate the low-carbon pathways to evaluate the impacts by income class, showing the adverse distributional impacts for low-income classes and the risk of "technology" and "energy" poverty, for each MS dynamically over time	E3M	# P4, P5
The next step is to assess policy options that aim at mitigating the adverse social effects using the GEM-E3-FIT model to ensure budget neutrality. The policy options will influence equipment choice by income class.	E3M	# P4
Based on distributional impact analysis, we will evaluate possible measures to reduce the cost burden on certain industrial sectors, which are energy-intensive and are strongly exposed to foreign competition. This is combined with the industrial leakage analysis of Task 4.1.	E3M	#P5
The work in this task will propose adjustments to the policy measures of the EU "optimal" pathway in order to alleviate social and other adverse	E3M, SPRU	#P4, #P5

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

effects and thus render the pathway more acceptable and manageable		
COVID-19 will be recognised, acknowledged and taken into account in the write-ups of Task 4.3.	SPO	#P3

In addition to the thematic areas specified in the task requirements and presented above, we have performed one additional research study to assess the distributional impacts of the Covid-19 pandemic and green stimulus programmes. This study was performed by INNOPATHS partner SPO, and aims to provide evidence on the distributional effects of a post-pandemic green fiscal stimulus, focusing on employment and wages of low-skilled manual workers (#P3). Finally, E3Modelling (E3M) performed an additional assessment of the socio-economic and distributional implications of the recent EU Green Deal targets (#P4, #P5), highlighting the main challenges facing the EU's energy-intensive and trade-exposed industries, and low-income classes, from the transition to climate neutrality by mid-century.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

B. Key Insights of the deliverable

In the following we present the key insights and messages emerging from the research papers.

B.1 Insights from Research Paper 1: Beyond the energy system: modelling frameworks depicting distributional impacts for interdisciplinary policy analysis

The research study (which has already been published as a scientific paper) synthesizes common modelling frameworks used to assess technical and environmental aspects in policy analysis and their recent progress to illustrate social and distributional impacts of energy and climate policies. The study presents the main indicators produced by each modelling method and includes a critical review pointing to gaps and limitations that could be addressed by future research.

Various modelling frameworks are used to simulate distributional impacts of climate policies

There is increasing interest in the analysis of social and distributional impacts of energy and environmental policies, as more ambitious policies (commonly in the form of imposing taxation on energy products) are implemented worldwide. Distributional effects refer to how the gains and costs of a project or policy are distributed among its participants, which in terms of policy-making may refer to different regions, sectors, and households. Distributional impacts are commonly associated with inequality, which may include differences in income and welfare. Ignoring possible distributional effects may result in less effective policies and even increased inequalities as climate policies, without mitigation measures, may induce regressive distributional impacts, disproportionately affecting disadvantaged population groups. Various modelling approaches are used in the scientific literature to simulate the distributional impacts of energy and climate policies, including energy system partial equilibrium models, input-output modelling frameworks, macro-econometric, general equilibrium models, environmental and microsimulation models. The fundamentals of each modelling framework are described to provide a complete view of the diversity of modelling tools available for energy and environmental policy analysis.

The comparative scientific assessment shows that the utilization of such modelling frameworks precedes the study of energy and climate policies in its modern transdisciplinary concept, so each method alone is only capable of capturing specific distributional effects associated with climate policy measures.

Integrated modelling approaches are required to appropriately assess the distributional impacts of climate policies

The study describes how distributional effects are traditionally considered in different partial and general equilibrium models (e.g. modelling research by geographic

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

scope, policies evaluated, sectors or actors modelled), and assesses the methods used to incorporate consideration for distributional impacts. We also review the strengths and weaknesses of different methods and their overall effectiveness in capturing social and distributional impacts and analyse various indicators that are used to measure them. The review shows that energy system models using a partial equilibrium formulation can be used to assess the technological requirements and costs of energy and environmental policies due to their high level of technical detail. However, the lack of feedback with other economic sectors constrains their use in climate policy analysis. The general equilibrium models are capable of accounting for feedback effects between sectors and regions in exchange for a less detailed technical description of the energy system. Environmental impact assessment models make it possible to estimate the health impacts of air pollution from fossil-fuel consumption for energy-related activities. Based on the scientific review, integrated modelling solutions are required to appropriately capture the social and distributional implications of energy and climate policies. However, due to the unique formulation of each modelling framework, it is a challenge to develop a comprehensive method that includes the energy, socio-economic, and environmental dimensions altogether. An integrated solution attempts to link two or more models (e.g. energy system, general equilibrium and microsimulation models) in a common framework to close the gap between different perspectives and mitigate the weaknesses of individual modelling techniques. The study shows that a common solution for the inclusion of distributional effects on modelling frameworks is the disaggregation of sectors or households, but this raises several challenges related to data availability and the difficulty in accessing household surveys that are required for the representation of multiple different household groups. Integrated solutions offer a pathway to reconcile the strengths of different modelling approaches, but literature is scarce on linking different model types in a unified framework that also considers different household groups.

B.2 Insights from Research Paper 2: Is time preference different across incomes and countries?

The subjective discount rate is a fundamental parameter in any economic model that describes problems of intertemporal allocation of resources, consumption or capital. Various factors, including income, wealth, education and culture, influence the degree to which individuals discount the value of future costs and benefits.

Large differences in time preference across countries and income classes

Theory predicts an important relationship between time preference and income and country-specific factors, and substantial amount of evidence has supported this hypothesis. The idea that income level is an important indicator of time preference has received strong empirical support with literature indicating an inverse relationship with discount rates related to individual consumption choices for energy efficient appliances. The inverse relation between time preference and income level is explained in the literature as a result of imperfect capital markets that prevent impatient low-income individuals from investing, but also driven by more deep-seated cultural and geographical factors.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Discount rates are higher for low-income classes

This study offers new empirical evidence on the relationship between time preference and income levels, by estimating discount rates for a set of six European countries across five different income classes, using time series data and calculating an explicit test of these differences. This estimation benefits from the use of a carefully-designed data driven procedure to select the Generalised Method of Moments (GMM) instruments, which are then combined together in a system GMM estimation. The econometric estimation finds overwhelming evidence of differences in time preference between countries conditional on the same income class, and a more varied picture as to the within-country differences across income classes, reflecting country-specific factors such as culture and institutions. Overall, the study confirms that the discount rate is highest for low-income individuals, which implies that low-income households should be supported with dedicated subsidies in order to perform the required investment in energy efficiency and minimise the potential adverse social and distributional impacts of climate policies.

B.3 Insights from Research Paper 3: Distributional effects of a post-pandemic green fiscal stimulus: skills, employment and wage of low-skilled manual workers

A green fiscal stimulus is prominent in the current policy debate aiming to support the economic recovery from the Covid-19 pandemic. Supporters of the green recovery argue green stimuli would boost GDP, create jobs and help redirect economic systems towards the strategic long-term goal of reducing emissions. This research study provides new evidence on the distance in worker skill sets between occupations displaced by Covid-19 and other structural shocks, and the subset of green-manual occupations that are expected to be in high demand as a consequence of a green stimulus.

Skill distance and other barriers may limit a transition of displaced workers to green manual jobs

The study analyses whether gaps in green skills across occupational groups might affect the impact of green stimulus investments, focusing on the likely losers from the Covid-19 pandemic and likely winners from a green fiscal stimulus (i.e. green-manual jobs). The study finds that low-skilled occupations exposed to social distancing measures introduced by governments in response to Covid-19 as well as automatable occupations possess a skill-set that is different from that required by green-manual jobs. On the other hand, low-skilled labour in emission-intensive industries could be more easily employed in green-manual jobs as they already possess an adequate set of green skills.

Areas with green training facilities gain the most in terms of green-manual jobs after a green fiscal stimulus

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

As gaps in green skills could be a barrier to replacing displaced jobs, training can be a solution as it provides workers with the skills required for performing high-demand green jobs. The study provides evidence about the role of localised green training as an enabling factor in the creation of jobs by means of green fiscal stimulus by exploring the American Recovery and Reinvestment Act of 2009. The analysis shows that the potential for creating green jobs as a result of green fiscal stimulus crucially depends on the availability of green training to close the skills gap between displaced workers and jobs in high-demand because of a green fiscal stimulus.

B.4 Insights from Research Paper 4: Assessing the social and distributional impacts of ambitious climate policies in EU

The increased ambition of climate policies would result in large-scale economic restructuring with potential regressive distributional impacts, disproportionately affecting disadvantaged population groups, which face high energy expenditures as a share of their income combined with difficulties in accessing low-cost funding. The imposition of additional taxes on energy products would increase the risk of energy poverty and other challenges facing low-income households. In this study, the state-of-the-art GEM-E3-FIT model is further expanded to represent ten income classes in EU Member States in order to consistently capture the potential distributional impacts of energy and climate policies.

Without mitigation measures, decarbonisation policy would entail regressive impacts on the income and expenditure of low-income households

Distributional effects refer to how the costs and benefits of a policy are distributed among its participants, which may refer to different regions, sectors, and households. Environmental policies are usually associated with regressive distributional impacts, disproportionately affecting low-income households. The research study is based on the enhanced version of GEM-E3-FIT, which is expanded to represent ten income classes in all EU Member States, by differentiating their income sources, savings and consumption patterns. Using these methodological and modelling advancements, the socio-economic and distributional impacts of the EU Green Deal policies and targets are assessed until 2050. Ambitious climate policies affect employment and labour income in European countries, showing a limited reduction in low-skilled labour demand combined with an increase in high-skilled jobs required for the low-carbon transition. This raises negative distributional impacts through the labour market leading to higher inequality levels, as quantified with the Gini and S80/S20 indexes. The implementation of the EU Green Deal targets would also increase the energy-related expenditure in households, especially for those of low-income, raising the issues of energy poverty and energy affordability as these income classes already spend a large share of their income to purchase energy services and equipment.

Negative social impacts to low-income households can be alleviated with appropriate use of ETS revenues

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Ignoring such distributional effects may result in limited social acceptance of the energy transition, less effective climate policies and even increased inequalities due to the lack of measures to mitigate negative impacts on vulnerable population groups. Well-designed strategies are required to achieve progressive outcomes of energy and climate policies by considering appropriate compensation schemes, either by increasing household income through lump-sum payments or reducing other (direct or indirect) taxes, or through the social security system.

The model-based assessment using the leading GEM-E3-FIT model representing ten income classes showed that income inequality caused by environmental policies can significantly decline if ETS carbon revenues are redistributed via lump-sum transfers to households and via reduced social security contributions. As we assume that the distribution of lump-sum transfers follows the distribution of social benefits and allowances to different income groups, the redistribution of ETS carbon revenues will significantly reduce income inequality bringing high benefits for low-income households in European countries. Overall, the research shows that the transition to climate neutrality may increase modestly existing income inequality, with low-income households facing more negative effects than higher-income ones. However, using carbon revenues towards lump-sum transfers to households and towards reduced social security contributions has clear benefits increasing total employment, while reducing significantly the inequality across income classes in European Member States.

B.5 Insights from Research Paper 5: Reducing the cost decarbonisation burden to EU energy-intensive industries

The implementation of unilateral climate policies would increase the production costs for European energy-intensive and trade-exposed industries, reducing their market competitiveness and potentially inducing their relocation to non-abating countries. The risk of carbon leakage has widely been recognised as a key issue in the EU climate policy debate, while recently the EU Green Deal has suggested the Border Carbon Adjustment as a measure to protect domestic industrial activities.

Without appropriate preventative measures, unilateral climate policies could induce relocation of energy-intensive activities outside the EU

The cost-effectiveness of unilateral climate policies inherently suffers from the lack of “where-flexibility”, while unilateral policies increase the risk of carbon leakage, i.e. the relocation of emissions to countries with weaker or no environmental regulation. Two main channels for carbon leakage are identified: the energy price channel where fossil fuel consumption increases in non-abating countries as international energy prices are reduced due to carbon pricing in abating regions; and the industrial competitiveness channel, through shifts in comparative advantage of EITE industries which are relocated to non-abating countries. In this study, we use the enhanced version of the GEM-E3-FIT model to quantify the cost burden imposed on domestic EITE industries as a result of ambitious policies. Alternative policy scenarios are simulated aiming to directly inform policy makers and explore the macro-economic and trade impacts of the most recent policy pledges, including the carbon neutrality targets suggested by the EU and China.

*“This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Grant Agreement No **730403**“*

In case of unilateral ambitious EU climate policies, the redistribution of trade in commodities between the countries as a result of changes in their relative competitiveness leads to a carbon leakage of 25% over 2025-2050, mostly towards China and India, while Russia also benefits due to the low transportation costs from EU markets. The size and composition of the economies participating in the climate group matters for the leakage rate, as an EU-China coalition leads to a significantly lower leakage rate. A key factor explaining the result is the high effectiveness of the carbon price to reduce emissions in countries such as China, which have significantly higher energy and carbon intensity and lower industrial production costs compared to the EU and other developed economies.

Among sectors, metal production and the chemicals sector experience the highest leakage rates, as they are characterized by high energy intensity and high trade exposure. In addition, large amounts leaked correspond to additional emissions in power generation, as increased industrial activity in non-abating countries requires higher amounts of electricity production, thus increasing GHG emissions given that the power mix in these countries heavily depends on fossil fuels. Measures focusing on reducing emissions in power generation in non-abating countries would greatly help reducing leakage without applying economy-wide carbon pricing.

In case that the EU and China join forces to reduce GHG emissions, the activity impacts are larger in the Chinese economy, as it has higher emissions and carbon intensity than the EU and bears about 85% of the overall mitigation effort. In this context, the cost competitiveness of European industries vis-à-vis the Chinese improves considerably, and thus EU industrial activity losses are very small relative to the Reference scenario. These results indicate that linking the carbon markets of EU and China reduces the international competitiveness of China's energy intensive sectors but increases the competitiveness of EU's sectors.

The implementation of Border Carbon Adjustment effectively protects European energy-intensive industries

The EU Green Deal has suggested the Border Carbon Adjustment (BCA) as a potential instrument to protect domestic industrial activities in the EU. As there are difficulties in implementing rebates of emission payments on exports from the EU, the BCA is implemented through tariffs on embodied emissions of goods imported to the EU from unregulated trading partners, in order to level the playing field between domestic and imported products with respect to carbon costs. The imposition of a BCAs can effectively reduce carbon leakage through trade in emission-intensive and trade-exposed industries, thereby attenuating adverse impacts for these sectors in the EU. The analysis shows that the BCA can be a complementary measure to domestic climate policy, while the adopted revenue recycling scheme is important, as using BCA revenues to reduce social security contributions is highly beneficial for domestic employment.

The study illustrates that while a BCA can be effective in reducing emission leakage and industrial relocation, careful consideration should be given to its design with particular emphasis on how the revenues are used while ensuring compliance with WTO rules. The BCA seems attractive under global efficiency and domestic political economy considerations, but legal and administrative barriers may substantially constrain the scope for efficiency gains through implementation of BCA.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Research paper 1: Beyond the energy system: modeling frameworks depicting distributional impacts for interdisciplinary policy analysis

Status of the research paper: *The Study has been published in the Energy Technology scientific journal*

Roland Montenegro, Panagiotis Fragkos, Audrey Dobbins, Dorothea Schmid, Steve Pye, Ulrich Fahl, Beyond the energy system: modeling frameworks depicting distributional impacts for interdisciplinary policy analysis, Energy Technology, 2020, https://onlinelibrary.wiley.com/doi/full/10.1002/ente.202000668

Abstract: Since the signing of the 2030 Agenda for Sustainable Development by the United Nations Member States and the Yellow vest movement, it is clear that emission-reducing policies should consider their distributional impacts to ensure a sustainable and equitable growth compatible with the Paris Agreement goals. To this end, the design of environmental and energy policies should be accompanied by an interdisciplinary analysis that includes potential effects on distinct groups of society (defined by income, age or location), regions and sectors. This work synthesizes common modelling frameworks used to assess technical, socio-economic and environmental aspects in policy analysis and the recent progress to portray distributional impacts in each of them. Furthermore, we highlight the main indicators produced by each method and present a critical review pointing to gaps and limitations that could be addressed by future research.

Keywords: distributional impacts, energy policy, energy system modelling, environmental impacts, general equilibrium modelling, model coupling, micro-simulation

1.1 Introduction

The consideration of distributional impacts in the analysis of the energy and environmental policies has risen in importance as more ambitious climate policies are implemented worldwide, often imposing taxation on energy products. Distributional impacts refer to the case when different household groups or individuals are affected by a policy to a different degree. Distributional impacts are commonly associated with inequality which may include differences in the environmental burden or distribution of income and welfare. A case that illustrates the negative consequences of not considering the distributional effects of climate policies is the Yellow vest movement that started in 2018 in France. The movement was marked by mass protests against the rising fuel taxes and prices and claimed that middle and working classes were paying a disproportionate share of the burden from the national tax reforms.[1] These protests are a sign of how the issue of inequality has grown in relevance in recent years and how neglecting this topic may hinder climate protection action. In the European Union, for instance, increasing levels of income and carbon inequality in a large number of Member States are causing concerns for both the sustainability of economic growth and social cohesion.[2] Globally,

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

the gap between rich and poor is increasing and in 2015 the wealth of the richest 62 people in the World was equal to that of the bottom half.[3]

To tackle the issue of inequality, the United Nations adopted in 2015 the 2030 Agenda for Sustainable Development, in which reducing economic disparities is one of the seventeen sustainable development goals (SDGs).[4] This agreement reinforces the need to provide a global solution for the problem of inequality and shows that policies aiming at sustainable development should consider their social and distributional impacts on different income classes and regions.

To this end, this work reviews the recent literature on the model-based methods utilized for policy analyses in the areas of economics, energy systems and environmental damages. Furthermore, we explore ways in which these models and methodologies depict distributional impacts, the main indicators obtained from their results, shortcomings of each modeling methodology and suggest improvements for future research.

1.2 Distributional impacts from energy and environmental policies

This section provides a short literature overview of possible distributional impacts of different environmental policies. As the literature on environmental policies and distributional effects is vast, we focus here on the main reasons why distributional impacts may occur and their relevance for environmental policy assessment.

Depending on the chosen policy instrument and the underlying socio-economic structure, distributional impacts of environmental policies may vary significantly, both between countries and within countries.[5–7] Overall, environmental policies are usually associated with regressive distributional impacts in literature, disproportionately affecting disadvantaged population groups. There is, however, also evidence for progressive impacts, especially in developing countries, where inequalities can be effectively reduced.[7,8] The focus and significance of distributional impacts vary depending on the unit of analysis, i.e., the spatial scale of the study, the chosen indicator(s) concerning inequalities considered and sectors/goods affected.[7] For a detailed discussion of possible distributional impacts of individual policies, the reader may refer to [7,8].

Evaluating distributional impacts of environmental policies should consider both financial implications, i.e., impacts on income and wealth distribution, and possible environmental benefits in the form of reduced environmental hazards or improved accessibility to environmental goods.[8] The latter is, however, difficult to assess quantitatively and may vary greatly on a geographic scale. Additionally, the relationship between a lower socio-economic status and higher exposure to environmental hazards is ubiquitous, especially within countries.[8,9] Thus, assessments of distributional impacts of energy and climate policies often concentrate on income distribution, neglecting possible benefits from reduced environmental inequalities or other indirect effects. Financial implications usually depend on the demand elasticities of the affected goods and possible budget or credit constraints associated with socio-economic status, e.g., different disposable income, owned assets, or accessibility to technologies.[7] Depending on how the policy is funded and on who consumes the affected goods, distributional effects may impact households, industries or states both negatively or positively. Well-designed strategies may also achieve progressive outcomes by considering appropriate compensation schemes, either by increasing household income through lump-sum payments or reducing other taxes, or by public investments, e.g., in infrastructure, or through the social security system.[5,7,8]

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

As distributional impacts of environmental policies depend significantly on the policy design itself, and at least partially on the geographic distribution of environmental burdens,[7] it is only possible to assess them on a case-by-case basis. Ignoring possible distributional effects may, however, result in less effective policies and even increased inequalities due to missing policies to mitigate potential impacts.[5,7,8] These are, however, often only included on a broader level in policy impact assessments without any detailed analysis of how different socio-economic groups are affected.[10] Existing policy impact assessment guidelines often only state that some social and environmental impact assessment should be conducted [11] and offer scope for interpretation regarding the depth of analysis and applied methodologies. Such contextual factors flow into the model design, which often ignores the complexity of distributional impacts by focusing predominantly on economic efficiency instead of equity.[5]

1.3 Quantitative methods and modeling frameworks dealing with distributional impacts

This section briefly introduces modeling frameworks linked to the analysis of the energy and climate policies and how they portray distributional impacts. However, as the utilization of these frameworks precedes the study of environmental policies in its modern transdisciplinary concept, each method alone is only capable of capturing specific effects associated with the measures mentioned above.

1.3.1 Energy System Models (partial equilibrium)

Energy system models based on a partial equilibrium framework take into account the economic activities of the energy sector or parts thereof. They, therefore, do not consider the implications of energy-related investments on other parts of the economy, e.g., labour or other investment requirements, in contrast to general equilibrium models.[12] The framework can be further categorized into simulation and optimization methodologies (such as PRIMES and the TIMES framework).[13,14] Optimization models aim to identify the least-cost solution and simulation models aim to replicate the development of a specific sector, accounting for the decision making of different actors. The general objective function of the optimization model relies on linear programming and minimizes the discounted total energy system costs, subject to various constraints (e.g., energy or emission balances, efficiency relationships, utilization constraints, reserve capacity, greenhouse gas mitigation targets, emissions, renewable quotas, etc.) as described in Equation S1.[13]

The techno-economic framework of the partial equilibrium models is typically applied to study the long-term effects of a transition to a low carbon economy yet often does not include consideration for distributional impacts.[15] Distributional impacts have typically been assessed through linking with other models, e.g., macroeconomic, or by increasing the level of detail in a sector through disaggregation.

1.3.2 Input-Output models

Input-output models (IOM) depict the interdependencies between different sectors of the economy. This framework illustrates how the output from one economic sector becomes the input for another sector and, thus, can cover direct and indirect price changes of different product categories.[6] The indirect impact of carbon taxation policies accounts for higher prices of goods and services using carbon-intensive inputs. This

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

approach commonly assumes that levies are fully passed through to the final consumers. The assumption of inelastic demand corresponds to the short-term incidence of higher prices.[16–19]

As these models have a bottom-up representation of the economy, they are capable of producing results on a regional level, such as changes in sectoral prices and production levels. In terms of distributional indicators with a focus on households, the models can provide changes in income and consumption induced by policies for representative households.

1.3.3 Macroeconomic models (general equilibrium)

Based on the input-output framework, multi-sectoral Computable General Equilibrium (CGE) models are powerful modeling tools to consistently assess the impacts of climate policies in different households. These models link the macroeconomic impacts from changes in prices, assets and productivity and capture all sources of income, consumption preferences and skill endowments of households. However, analysing the implications of climate policies for poverty and income distribution requires that such models explicitly represent different household groups and their heterogeneity in terms of:

- factor endowments, such as differences in financial assets or labour and skills supply across households;
- preferences and savings, commonly achieved by differentiating parameters in households' utility functions (e.g., preference shares, substitution elasticities) to simulate different decisions of household types on saving vs. consuming;
- wage rates and different return rates to capital for different households (e.g., imperfect capital markets like credit rationing according to income), but also household decisions on participation in the labour market depending on their specific characteristics.

An overview of the mathematical formulation of CGE models is given in the supporting information in Equations S2, S3 and S4.

1.3.4 Environmental models

Environmental models are primarily used to estimate the possible environmental impacts of technologies and policies. Environmental impact assessment is conducted regularly as part of a standard policy assessment to avoid any unwanted side effects and identify effective and efficient environmental protection strategies. The applied simulation models often follow the Impact Pathway Approach to relate socio-economic activities to possible environmental outcomes. [20] Due to the involved complexity and variety of potential environmental issues, a myriad of models exists, focusing on different impact categories, geographic scales and sectors as potential polluters. In contrast to economic models, environmental ones do not focus on financial implications, but try to capture possible impacts of policies on inequalities regarding the exposure to environmental hazards, which may not be possible to be reflected in monetary terms.[8] Depending on their setup and chosen methodology, environmental models may be used to assess distributional impacts of policies on different spatial resolutions and across sectors, population groups, or individuals.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

1.3.5 MicroSimulation Models

Microsimulation models account for behavioural changes by considering consumer choices.[6] In this framework, consumers maximize their utility for a given set of preferences, prices and budgets, while considering their demand to be elastic. Commonly used methods include the Almost ideal demand systems (AIDS),[21–23] the Quadratic almost ideal demand system (QUAIDS),[24–26] the more recent Exact affine stone index (EASI) demand system[27,28] and the Engel curve model.[29]

These models are capable of assessing policy effects on each modelled household, which can easily be as numerous as the number of respondents in national household surveys.[30] These effects include tax incidence, changes in consumption and income level. Additionally, they are also used to produce estimations on the levels of (energy) poverty as a result of the policy being analysed.

Despite focusing on individual level modeling, as in agent-based models (ABM), microsimulation models produce a rich detailed data description of individual behaviours while often lacking the interaction and feedback among individuals.[31] On the other hand, ABMs seek to analyse the interaction and feedback between individuals and how it affects their behaviour.

1.4 Distributional impacts in individual modeling frameworks

This section discusses in more detail the methods, data requirements, advantages and limitations of the three main modeling frameworks: partial equilibrium, macroeconomic and environmental impact assessment models.

1.4.1 Energy System Models (partial equilibrium)

This section describes how distributional effects are traditionally considered in specific partial equilibrium energy system models. The review explores different modeling research by geographic scope, policies evaluated, sectors or actors modelled and the methods employed to incorporate consideration for distributional impacts. This is followed by an assessment of the strengths and weaknesses of different methods and their overall effectiveness in capturing distributional impacts. Various indicators are used to measure the distributional impacts. This section concludes with an overview of the usefulness of this type of modeling framework for assessing the distributional effects of climate policies.

Methodologies to assess distributional impacts of energy and climate policies

Partial equilibrium analyses based on an optimization modeling framework aim to identify the least-cost pathway and the development of technology diffusion under policy targets across the whole energy system. The framework aims to balance prices and quantities across one or more markets to the point of equilibrium between energy supply and demand. Concerning distributional impacts, a key limitation of this methodology is that it only considers what occurs within the energy system boundaries. Consequently, there is no inherent feedback loop to better estimate the impacts on the broader economy, e.g., increased energy costs, or the collection and distribution of carbon taxes. A second issue concerns the focus of such a framework on technological and economic factors, where the primary objective is to identify longer-term technology pathways towards achieving specific policy targets with limited focus on the role of policy design in the

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

near term and sectoral implications of policy interventions. A more aggregate representation of sectors means that socio-economic differences within sectors are not often represented. A third issue is the optimization paradigm. This approach strongly favours the economic efficiency of a solution with less appreciation of the inertia and barriers inherent across different sectors, and differences between actors. Given their techno-economic focus, the simplification of behavioural representation, and the long-term analytical time frame, such models are less able to simulate the impacts of sector-specific policies, and their distributional impacts.[15,32]

Sabio et al. [33] conducted a review to assess the potential of long-term energy system models to address the distributional impact deficit. This study reinforces the point that traditionally, the impacts on households are difficult to be determined with the standard partial equilibrium model structure for the reasons listed above, but particularly noting the issue of aggregation to 'typical' households. For the residential sector as an example, this means a focus on disaggregation based on physical building stock but without reference to heterogeneity across individuals, groups or households. As a result, the differentiated impacts on this heterogeneous sector are negated.

In re-thinking how such models could be used for distributional impact analysis, the objective would be to capture insights to determine the impact on economic dimensions (e.g., cost distribution), social dimensions (e.g., well-being, energy welfare) and the overall impact on marginalized and vulnerable groups.[34] As per [33], two approaches are considered for the assessment of distributional impacts using partial equilibrium models, namely, disaggregation and linking sector models. A third approach includes off-model interpretation of scenario metrics to understand distributional impacts using complementary datasets, referred to as an equity evaluation.

Model disaggregation

This approach allows for the explicit definition and consideration of particular socio-economic groups according to their specific circumstances (income, building, tenure, number of people, etc.) within the model framework.[35] The additional heterogeneity in the model provides a basis to assess the differentiated impacts on different groups within a sector.[15] Including disaggregation has become more common in partial equilibrium models as a means to gaining more insight into the behavioural aspects of investment and consumption, but without necessarily focusing on determining the distributional impacts of policies.[36–38] The TIMES-GEECO model applied to Gauteng in South Africa used disaggregation to better reflect the heterogeneity of the household sector by socio-economic factors - and, therefore, the ability of different groups to comply to energy and climate policies.[36,39] A similar approach is applied in the developed country context, where households are disaggregated by various parameters, including socio-economic characteristics around income, building type, tenure.[39,40] The TIMES Actors Model (TAM)-household sector model includes the disaggregation of different socio-economic profiles of households but also uses this structure to evaluate the impact of different carbon taxes.[39] However, as this approach is not coupled with a macroeconomic model, the impacts reflect only partially the cost implications of policies on a specific actor, household, or sector. Doda and Fanhauser [41] applied a deterministic partial equilibrium model to assess the often-neglected distributional impacts of climate policies on the supply side. The policy instruments evaluated include emission reduction policies on power suppliers, such as carbon pricing,

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

taxes and subsidies, which also investigate subsidy schemes and their impact on household welfare for specific technologies.

Linking sector models

A second approach for incorporating distributional impacts into energy system models is via linking sector models. The benefit of linking is that the energy system model does not have to be disaggregated but can retain its current structure and link to another model such as a CGE (to assess wider economic impacts) or micro-simulation model for detailed sectoral analysis. The process of linking sector models is done either through coupling, soft-linking or hard-linking. Coupling involves running models separately and exchanging key variables such as energy prices and demands to reach equilibrium. Soft-linking includes the use of an intermediary model or an exchange of common parameters. Hard-linking entails integrating one model into another and demands a high level of modeling skills and reformulation of the model objectives, source code and underlying database.[42] The types of models commonly linked to the partial equilibrium models include general equilibrium models, micro models and other economic models, as discussed in Section 5.2.

Equity evaluation

The third method works with partial equilibrium models as structured, but incorporates consideration of distributional impacts in the scenario definition process and/or undertakes analysis on the model result metrics through the use of complementary datasets, i.e., interprets scenario results through distributional impacts lenses. On the scenario definition approach, Chapman and Pambudi[43] apply a mixed-methods approach, which involves identifying preferences and social equity variables from surveys and then defining scenarios to be evaluated through energy system modeling. The results are then analyzed according to weighted factors for sustainability and social equity.

On the post-processing approach,[34] propose the InVEST approach to estimate the vulnerability of different regions and groups from different low carbon pathways quantified through the TIMES PanEU model. This analysis first mapped out subnational regions using metrics to capture vulnerability under a low carbon transition, e.g., regions with higher levels of energy poverty, regions dependent on energy-intensive industries and/or hydrocarbon extraction. Based on the regional picture of vulnerability, the next step was to consider how different low-carbon pathways might impact on such regions and communities if such vulnerabilities were to persist in the future.

Various studies have used methods such as model linking and disaggregation, but few have applied them to address distributional impacts specifically through a partial equilibrium energy system model. The strengths and weaknesses of these methodologies in relation to distributional impact analysis are summarized in Table 1.

Data, metrics and limitations

The model disaggregation approach requires additional datasets for capturing differences between households in the model, with a focus on socio-economic factors and their linkage to the energy system, e.g., how much energy they consume, age of

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

appliances and building envelope, household condition, dwelling ownership, access to personal mobility.[15] The challenge is that this approach is very data-intensive. Furthermore, often socio-economic datasets are not linked to the physical energy system. For example, understanding the dwelling profiles in a model by socio-economic category is often challenging due to limited data. A further challenge concerns how socio-economic factors may change over time. This issue can be handled by exploring alternative scenarios. Finally, the data required are dependent on the specific distributional impact question. Distributional impacts are related to many different socio-economic variables. A particular challenge for partial equilibrium models concerns spatial resolution, and therefore exploring regional differences would be problematic. A key question is balance; these models answer different questions and therefore ensuring tractability while building in distributional impact analysis capability is critical.

Fell et al. [15] undertook a useful exercise to ask stakeholders about the utility of such an approach. There was a pragmatic recognition that such models would never be able to capture all issues related to distributional impacts and that large uncertainty would exist when applied to long term analysis. While the approach was considered to have potential, stakeholders suggested to focus not only on identifying distributional impacts but could also provide policy insights around different pathways. Key challenges remain for this approach around data - and the suitability of the framework for this type of analysis. However, this should be balanced against the importance of ensuring that distributional impact analysis is recognized in long term pathway analysis.

The linking approach essentially allows for separate models to exchange data and information between each other. Linkages to CGE models are fairly well understood, whereby energy cost increases are fed from the partial equilibrium model to the CGE model, with feedback in respect of energy demand levels. Linkages to micro-simulation could involve metrics such as energy costs, carbon prices, and energy demand levels, providing the boundary conditions for the sector level assessment. A key challenge is the consistency between models and the level of complexity in moving towards a hard-linked framework.

Finally, on the equity evaluation approach, Pye et al. [34] provide insights into the metrics used from the partial equilibrium model to further explore vulnerability and distributional impacts. These focused on the energy cost burden on different industries and households under different scenarios, and the levels of investment needed. Both metrics highlight positive and negative impacts, and the requirements for policy interventions. In terms of vulnerability indicators on which to map the scenario metrics, these include energy intensity of industries, energy poverty levels, and employment in carbon-exposed industries. For example, statistical indicators around vulnerability in households aimed at assessing the level of energy poverty show a household or region is already vulnerable to energy cost changes as exemplified in Figure 1. The expenditure varies widely by regions but also within a region by income group.

The metrics give an indication of whether households would be disproportionately burdened when looking at the required per household investment costs resulting from the model for a specific scenario. These insights mainly point towards the types of technologies that will be required and give insights to the policy interventions that will be needed to avoid potential detrimental impacts on vulnerable households, industries or regions - depending on the geographical or sector scope of the model.

Final remarks

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Energy system models are limited by the lack of behavioral representation, including heterogeneous actors and the lack of linkage to the wider economy. While there is a live debate as to whether such models should be applied to distributional impact analysis, a number of approaches do offer some possibilities. These include further disaggregation of energy models to capture the heterogeneity of households, linking to more detailed sector models, and finally additional interpretation of model outputs based on a careful definition of scenarios with relevant indicators. Without further research into the prospects of such approaches, the analyses by energy system models risk ignoring critical issues of equity of transitions and the distributional impacts that arise. Given that such issues are fundamental to a successful low carbon transition, more research on the merits of these approaches are needed.

1.4.2 Macroeconomic models

This section reviews methods to depict distributional impacts in macroeconomic models based on the general equilibrium theory. We start by giving an overview of macroeconomic modeling applied to evaluate the distributional effects of energy transition and summarize commonly used techniques to portray these effects in the general equilibrium framework. The description of each technique is followed by a critical assessment of its data requirements, strengths and weaknesses. Despite not being the focus of this work, but given their importance, the last part of this section briefly comments on the application of IOMs for the analysis of distributional impacts.

The main advantage of using macroeconomic models, compared to energy system models portrayed in the last section, is that general equilibrium models can represent the entire economy. This feature allows for feedback effects between the energy system and other sectors of the economy.

Introducing household heterogeneity into CGE models for the analysis of distributional effects dates back to the 1970s when Adelman and Robinson analyzed income distribution policies in South Korea as a case study.[44,45] The addition of this feature better reflects the fact that households have distinct utility functions, labour types (skilled/unskilled), capital endowments and consumption patterns and allows for the analysis of socio-economic effects such as poverty, income distribution, the incidence of taxes and social equity.

In recent years, macroeconomic models are being utilized to depict distributional effects due to their flexible formulation, which allows for an efficient implementation of household heterogeneity. This feature was applied in global models[46–48] by characterizing a representative household on the basis of underlying changes in age, household size, or urban-rural status, to analyse the effects of demographic change on economic growth, energy use and emissions. The inclusion of multiple household groups in global models can be performed by extending the number of household types for several countries or by performing a sequential microsimulation.[49,50]

Most of the methods to integrate income distribution in general equilibrium models have been developed in the context of development economics.[51–53] However, this strand of literature mostly uses static CGE models and analyses short-term poverty impacts of development-related policy shocks and does not account for several factors that are relevant for long-term climate policy assessment such as education and productivity development.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

1.4.2.1 *Direct Modelling of the income distribution*

This methodology, as shown in Figure 2, utilizes a predefined relative income distribution function to describe the income heterogeneity within one or more representative households and can be used to assess the changes in income for different households and number of people or households in risk of poverty. As shown by Boccanfuso,[54] this function can be modeled according to an existing distribution function (e.g. log-normal and gamma), or fit to a specific distribution data, such as household survey data.[30]

While this method is rarely utilized for climate policy analysis, Van der Mensbrugghe [55] used it to assess the long-term effects on the income distribution of the Shared Socio-economic Pathways (SSP), which are extensively used for climate policy assessment.

Groot and Oostveen [56] analyze the effects of energy subsidy reforms on welfare in selected countries by assuming income to be lognormally distributed. Results indicate that eliminating subsidies yields more budget-saving than the cost of compensating the population for the price increase. Also, countries that currently apply energy subsidization schemes could benefit from reforming them.

Data issues

Since this method focuses on the distribution of income, the data requirements are lower than other approaches. Additionally, from an income level survey, it is possible to derive the parameters for the probability distribution functions.[54]

Limitations

The results of this method depend strongly on the quality of the utilized income data and income distribution, especially considering the tails of the sample (richest and poorest households). Additionally, the distribution function is often kept constant over time. While this effect is negligible for short-term analysis, it should be considered for long-term studies when distribution functions can change significantly.[30]

1.4.2.2 *Representative Households*

In this methodology, as shown in Figure 3, the number of households is extended from a single representative household (used in conventional CGEs) into several representative household groups. Each group is individually described to account for heterogeneity in aspects such as labour supply, capital endowment and consumption preferences. This strategy maintains the structure of the CGE model relatively unchanged, except for the increased number of households that are modelled integrally in the CGE framework. The model then produces specific results for each household group in terms of income development, tax incidence, savings and consumption. The number of representative households can vary from a few to a couple of thousands and the choice of the number depends on computational, data, or application-specific considerations .[30]

Feng et al. [19] divide the household sector into income deciles to analyze the distributional effects of carbon taxation and four revenue recycling options in Taiwan. When compared to the case of no carbon taxation, using tax revenues to reduce labour

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

taxes resulted in an increase of 1.3% of GDP in 2050, not recycling the revenues led to a GDP reduction of 0.2% and direct redistribution to households with a higher share to low-income earners reduced GDP by 0.1%. On the other hand, the latter option produces the highest reduction in inequality.

Orlov [57] investigates the distributional effects of eliminating subsidy on gas consumption in Russia using a dynamic, multi-region, multi-sector CGE model with the electricity sector disaggregated into key technologies and 10 representative household groups (i.e., income deciles). This work suggests that using the additional revenue from higher domestic gas prices can alleviate income inequality in Russia and increase the total private consumption of the poorest decile by 3%. However, the most efficient revenue-recycling scheme is to invest in the energy efficiency of buildings, which have the largest energy-saving potential in Russia, leading to higher reductions of GHG emissions while increasing the consumption of the poorest decile by 1%.

Cunha Montenegro et al.[58] use a multiregional recursive-dynamic CGE model to analyze the impacts of long-term cap-and-trade policies on the EU Member States among four scenarios with different levels of decarbonization. The households of the EU-MS are divided into income quintiles and the revenues from the cap-and-trade policies are redistributed to the households in the same proportion that it occurred in the base year of 2011. Results indicate that increasing the reduction targets in the EU leads to a higher increase of income in low-income households compared to high-income households. However, the magnitude of income distribution varies per member Stater.

Rausch et al.[59] used a static CGE model for the US that includes 15,588 household types, to analyze the impacts of a 20 USD/tCO2 carbon price under three different revenue recycling scenarios. They found that the variation in impacts within broad socio-economic groups may swamp the average variation across groups, highlighting the relevance of including household heterogeneity in climate research.

Data issues

As stated by [30], a relevant issue to this method is that data concerning consumption, assets and incomes of households can deviate considerably between household survey data and national accounts. For that reason, it is necessary to reconcile data obtained from household surveys with national social accounting matrices (SAM), on which CGE models are usually based.

For dynamic model runs, one should also consider the development of each representative household with time. As time passes, the composition of education level within each group changes, there is migration among regions, the population structure changes and fiscal policies adapt to the demography of the population. These phenomena require their own set of assumptions (which are commonly decided by the modelers), increasing the data requirements for this methodology.

Limitations

Implementing multiple representative households in a CGE model results in increased computational demand and higher running times to solve. Therefore, one needs to consider this limitation when choosing the number of representative groups that fit the computational power available and meet the requirements of the analysis being made.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Another limitation of this method is related to the fact that the income distribution within each representative household is not modeled. By disaggregating the households into groups of equal size and ordering them according to income levels, e.g. in quintiles, the income level of each new representative household is the average of all the households in this group ("representative household"). However, the average income level can still present substantial deviations from the extremes, especially when considering the poorest and richest income groups. Therefore, the method is not well-suited to explore the impacts of climate policies on the poorest 1% of households.

1.4.2.3 *Final Remarks*

The methods to analyse the distributional impacts of climate policies using CGE models have varying data requirements and may produce diverging results, as they consider the interactions between household types and the rest of the economy in different ways. GCE models that integrate multiple households in their structural formulations produce detailed output for heterogeneous households while fully considering the interactions and general equilibrium effects between the household types and the economy. On the other hand, micro-simulations can provide detailed outcomes for a large number of household types but do not cover interactions among households. Direct modelling of the income distribution can be implemented with limited data available but does not deal with structural changes or any interactions between households and/or with the economy. The assessment of long-term distributional implications of climate policies requires capturing the heterogeneity in capital endowment and accumulation as well as differences between household types in consumption patterns and responses to price changes. To capture these effects consistently, methodological developments are required beyond the current applications of these methods in (mainly) static models.

The inclusion of multiple household types in CGE models would enable producing scenarios to explore the impacts of climate policies on household income and consumption, considering the interactions among households and between households and the economy. The micro-simulation methods can provide similar information as increasing the number of household types within the CGE model, but potentially for a larger number of household types with fewer computational limitations. The arithmetic micro-simulations enable developing comprehensive income distribution scenarios and account for the full impacts of climate policy on different household types. Behavioral microsimulation methods add to this as they account for changes in the labour force decisions of households which are important for long-term climate policy analysis.

1.4.2.4 *Distributional impacts in input-output models*

Leontief first presented the input-output model (IOM) in 1936 when he created a table representing the economy of the United States in 1919, which depicted the mutual interrelations among industries in that country.[60] IOMs rely on tables that describe sale and purchase relationships between producers and consumers, where rows represent supply and columns the demand.[61] Since these tables are fairly accurate in their depiction of inter-industrial relationships, they have been used extensively used by economists, environmentalists and policy makers.[62] On the other hand, IOMs also present limitations due to their simplistic nature, most notably the assumption of fixed coefficients of productions which ignores the possibility of factor substitution.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

The disaggregation of households in IOMs for the analysis of distributional impacts is rather straightforward and consists of using household expenditure survey to disaggregate the final consumption into the desired representative groups, often requiring matrix balancing techniques to ensure harmonization between the input-output table and the survey.[63,64] However, as observed by researchers in the 1960s, it is necessary to consider households as heterogeneous entities who have distinct consumption patterns.[65] To address this issue, Miyazawa[66] developed an extension to the IOM by introducing an inter-relational multiplier which computes how direct changes in income of one group results in indirect and induced income changes in another.[67]

Recent applications of IOMs go beyond the monetary framework and include physical units to better portray the energy and environmental systems. Zhang et al.[64] use an IOM with hybrid units and different income groups to investigate the effects of a CO2 tax on the Chinese economy and the results indicate that while this instrument is successful on reducing emissions with little impact to GDP, the effect on households is regressive and the most affected group are low-income rural households. Ramos Carvajal et al.[67] also uses the Miyazawa model to analyze the expansion of renewable distributed generation of electricity in Spain and suggests that increasing wind and solar electricity generation has the potential to decrease electricity prices and generate a positive impact on households' income.

1.4.3 Distributional impacts on environmental impact assessment models

In contrast to macroeconomic and energy system models, environmental impact assessment models do not necessarily deal with direct distributional impacts in the form of financial implications but focus on estimating the distribution of the environmental burden associated with specific policies. There has been a lengthy discourse in the literature regarding if and how environmental burdens relate to socio-economic status, thus affecting inequalities, especially in the case of air pollution and its impacts on human health.[8,68–70] Results regarding the direction and significance of such a relationship are, however, mixed. Hence, distributional impacts of energy and climate policies reducing the environmental burden may depend on the geographic scope, chosen socio-economic characteristics and considered environmental risks.[5,8,69–71] This ambivalence is also reflected in the variety of applicable models. The following provides examples of available modeling frameworks and discusses their advantages and limitations.

1.4.3.1 ***Methodologies to assess environmental impacts of policies and their distributional implications***

Since air pollution directly relates to the energy sector and constitutes the biggest environmental hazard for human health,[9] most impact assessments of energy policies tend to focus on air pollution as their main environmental indicator. Most modeling frameworks in this field follow the Impact Pathway Approach, which links the release of emissions through exposure assessment to pre-defined impact categories.[20] Since air pollution varies locally with meteorological and geographical conditions, spatial analysis and disaggregation offers itself to study distributional impacts. It is also possible to study distributional impacts between representative population groups. By introducing Agent-

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Based-Modelling, behavioural reactions to climate and energy policies may also be considered (e.g., a shift in transportation modes). These three concepts - spatial disaggregation, representative population groups and Agent-Based-Models - are shortly introduced and discussed in the following.

Spatial disaggregation

Since environmental impact assessment models are primarily designed to simulate and estimate changes in the spatial distribution of the environmental burden, distributional impacts on a spatial scale are often considered implicitly. The IPCC impact assessment [60] for example, discusses in detail how different countries may be affected by climate change, based on the spatial variation in temperature and meteorological conditions.[72] They conclude that the most vulnerable countries would suffer the most and thus profit the most from climate change mitigation. Such environmental benefits may even offset additional costs.[73,74]

Kitous et al.[73] analyze possible co-benefits from reduced air pollution due to increased climate mitigation on a global level. Although changes in concentration levels are modeled with a spatial resolution of 1°x1°, the analysis concentrates on the country level. Countries like China and India seem to profit most from additional climate change mitigation efforts, indicating that there are distributional impacts on the country level. Similar results are also provided by Vandyck et al.[74], who applied the same modelling framework.

The same methodological setup is applied as part of the policy impact assessment of the European long-term strategy “A clean planet for all”.[75] This study applies the GAINS model,[76–78] which is developed to assess compliance with air pollution control legislation and models air pollution down to street level. Although this modeling framework allows studying distributional impacts between countries, or cities, the policy impact assessment focuses only on the EU level, ignoring any possible effects between or within European countries.

SHERPA is another modelling framework suitable for policy assessment, which is specifically designed to analyze the impacts of different emission sources, i.e. sectors and neighbouring regions, on air pollution levels in cities and/or administrative areas.[79–81] With its spatial variability, it provides a flexible and easy-to-apply tool for policy-makers to study the distributional impacts of air pollution mitigation policies between different administrative areas. Spatial variance in the environmental burden within a city can, however, not be analysed as also acknowledged by Pisoni et al.[82]. For this purpose, dedicated city models, such as DIDEM, are required.[83] DIDEM has been specifically developed to study the impact of extending the district heating network in Torino. Although total emission may even rise, the city benefits from improved air quality and reduced associated impacts by relocating emissions from the city centre to a rural area.[84] This example shows the relevance of spatial distribution of both emissions and population when it comes to environmental impacts. While the people in the city centre benefit from better air quality, people living next to the new district heating plant may be affected negatively; yet due to the higher population density in the city centre, this is still considered a beneficial policy as indicated by a cost-benefit analysis.

The spatial distribution of the environmental burden does, however, not provide any information on the type of distributional impact, i.e. whether a policy has regressive

*“This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Grant Agreement No **730403**“*

or progressive impacts. For this, we also need to correlate exposure to some socio-economic indicators.

Representative population groups

One way to link environmental burden to socio-economic indicators is to define representative population groups and estimate their exposure to environmental risks in different microenvironments based on time-activity patterns.[85–88] Li et al.[86,87] showed that lifelong exposure to different environmental hazards varies significantly between population subgroups differentiated by age, gender, employment level and degree of urbanization, with characteristic behavioral patterns, such as smoking habits and time spent indoors. People living in areas with higher population density, for example, are usually exposed to higher ambient background concentrations. There is also evidence that low-income households show higher exposure to environmental hazards as they spend more time indoors, have usually smaller average room sizes and tend to smoke more often.[89] Gens et al.[85] used a similar model setup to study possible distributional impacts of improved insulation of buildings, which is supposed to reduce ambient air pollution through reduced energy consumption but may affect indoor air quality negatively due to a tighter building envelope. Though a tighter envelope also means less penetration of outdoor air, if significant indoor sources, such as fireplaces, cooking or smoking are present, their increased concentration levels due to lower air exchange rates may outweigh any benefits related to ambient air quality. Due to the time spent indoors and associated activities, insulation measures may thus have negative impacts on low-income households.[90]

Estimating exposure for representative population subgroups allows to include distributional impacts within countries or administrative regions in environmental impact assessments. Results may, however, differ, depending on how the subgroups are determined, i.e., which socio-economic characteristics are considered. As discussed in Li et al.[87], different environmental hazards may correlate with different socio-economic characteristics. Population subgroups are usually determined based on micro-census data; its availability determines, in the end, the spatial resolution of the analysis. Also, this data often only contains information about the location of residency, but not about where people work. For simplicity, it is often assumed that ambient concentration levels at the working place are the same as at the residency, ignoring possible distributional effects resulting from moving between different locations. One possible improvement could be to include data from GPS tracking.[91] Combining time-activity patterns with GPS location could allow to estimate individual exposure based on ambient environmental data with a high spatial resolution. The socio-economic characteristics of subgroups have to be matched to time-activity patterns, which are usually based on time use surveys. These surveys provide static diaries with additional socio-economic information. To avoid biased results, the models are usually run in a Monte-Carlo simulation to capture uncertainty, iterating through different possible diaries, resulting in an exposure distribution for each subgroup. Since these diaries are, however, exogenously determined, the models are not able to capture any behavioural reactions. With improved building insulation, for example, people may open windows more frequently as they notice a decline in indoor air quality. Similarly, better access to public transport and cycling lanes will affect the decision to travel by private cars. To also capture these responses and their

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

impact on the environmental burden, especially in cities, agent-based exposure models were recently developed.

Agent-based models

As described in Vallamsundar et al., Chapizanis et al. and Yang et al.[92–94] agent-based modelling (ABM) is used to estimate the dynamic exposure of population subgroups or individual agents to environmental hazards by combining, for example, air pollution maps with street and building information and an ABM layer. The ABM simulates the movement (behavior) of different agents according to their socio-economic characteristics and associated behavioural rules. Agents then react dynamically to changed situations, e.g. closed roads or improved public transport. With this approach, it is possible to also account for spatial variations in exposure and their distributional impacts within administrative areas. The modeled agents depend on the available information and data regarding time-activity patterns, socio-economic status, movement profiles and considered microenvironments. Additionally, decision-making rules may differ in each microenvironment or from region to region. Due to high data requirements, ABMs are usually only applicable to smaller domains, such as individual cities. Their current application seems to also focus on policy implications in the transport sector due to its dominance in urban air pollution. By considering dynamic exposure of different population subgroups, ABM frameworks may help policymakers to identify vulnerable subgroups and design better, targeted mitigation policies, effectively reducing distributional impacts. Despite their potential and flexibility, their suitability for policy analysis could be limited due to their complexity and missing knowledge on how socio-economic status affects mobility or consumption patterns in different regions or administrative areas.

1.4.3.2 ***Data, metrics and limitations***

Environmental impact assessment models require a lot of data. This data dependency increases the more detailed distributional impacts are to be studied. To differentiate population subgroups, spatially resolved population data has to be combined with socio-economic characteristics, e.g. from micro-census data, often only available on a coarser resolution (census or administrative level) due to data protection issues. Besides having to fuse different spatial scales and match different socio-economic differentiation, policy assessment is usually done prospectively and thus requires projections for future years. Available population projections consider changes in age distribution due to changing life expectancy and birth rates and partly also spatial changes due to increased urbanization. It is, however, not possible to project the distribution of socio-economic characteristics without introducing a substantial amount of new uncertainties. Though changes in socio-economic characteristics such as employment and income level may, for example, be determined by sequential analysis,[86,87] high uncertainties and increased complexity may result in difficulties to interpret the policy assessment results.

Improved exposure assessment considering different microenvironments additionally requires information about time-activity patterns. These are usually derived based on diaries, constituting only a snapshot in time of typical activities, which may also change in the future, also as a response to policies. Without modeling this change in activities, e.g. with ABMs, or considering such implications in the scenario setup, these behavioral responses are neglected in the analysis. Relevant information linking socio-

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

economic characteristics to activity/movement patterns and to derive corresponding decision rules could be collected from wearable sensors[95] or by coupling with other models, e.g., energy system models, transport models, or economic models with a suitable disaggregation, especially with regard to households.

1.4.3.3 *Final Remarks*

Environmental impacts are often modeled with a high spatial resolution that would allow studying distributional impacts on a spatial level, e.g., between neighbourhoods, but the analysis is often carried out only on a more aggregated, administrative level. Thus, most policy assessments focus on differences between countries, ignoring potential distributional impacts within countries due to changes in the environmental burden. Available frameworks to analyze these distributional impacts on population-level are characterized by high uncertainty and depend on available data quality. Static approaches based on simulating exposure in different microenvironments according to time-activity patterns can only provide a snapshot of possible distributional impacts. Assumptions about changing activities in the future need to be explicitly included in the scenario setup. ABMs offer the possibility to also consider behavioural feedbacks, i.e. changes in activities, but only as long as decision rules are known. Additionally, ABMs are potentially limited in their spatial domain due to increased data requirements. Finally, all discussed frameworks do not consider any financial implications of reduced environmental burden. Although health impacts are sometimes expressed as external costs, their financial implications with regard to distributional impacts are often not discussed. As mentioned in [8], not all environmental impacts can be expressed in market-relevant terms. If they are, however, it is possible to also feed their implications back to economic models. Less work loss days resulting from improved air pollution, for example, could increase labour availability in CGE models.[75] Including air pollution costs in energy system models may affect the energy transition pathways,[96] and thus have direct distributional impacts. By coupling environmental impact models with economic models would allow studying both the environmental and financial dimensions of distributional impacts or energy or climate policies.

1.5 Integrated Solutions

The previous sections have shown how distributional impacts of energy and environmental policies can be integrated into energy system models, macroeconomic models and environmental models. However, due to the unique formulation of each modeling framework, it is a challenge to develop a comprehensive method that includes the energy, socio-economic and environmental dimensions altogether. An integrated solution attempts to link two or more models in a common framework to close the gap between different perspectives and mitigate the weaknesses of individual modeling techniques.

While the process of linking two or more of the aforementioned models is not new and is further reviewed by Korkmaz et al.[97], cases applied to the investigation of distributional effects among households are still scarce. For this reason, we focus this section on two existing strategies: i) linking macroeconomic and micro-simulation models, and ii) linking partial equilibrium models with other models.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

1.5.1 Linking macroeconomic and micro-simulation models

Micro-simulation models may include a very large number of household types, even considering all households from a sample survey as separate household types. These models can vary widely in sophistication and granularity, ranging from simple accounting/arithmetic methods to approaches that include behavioral responses of households to changes in labour markets and product prices (i.e. changes in savings behavior). The micro-simulation and the macroeconomic models can operate in a sequential (top-down) form or in an iterative format (top-down/bottom-up), in which there is a feedback loop between the models,[30] as depicted in Figure 4.

1.5.1.1 *Sequential Approach*

In sequential studies, changes in labor and capital markets and consumption are first determined in the CGE model and are then integrated into the Micro-Simulation model as exogenous variables, which is then used to determine the impacts on households.[98] These are based on a set of equations quantifying income, expenditures, taxes and savings for different household types constrained by the survey data and CGE model results. These models usually include a detailed representation of taxes and transfers, and determine income of different household types.[99] Commonly, several output variables of CGE models are used as inputs to Micro-Simulation models, which can disaggregate the results over multiple household types, including wages, prices of goods, consumption, the sectoral composition of labor, etc.[100]

In addition, some modeling approaches include behavioral equations, which determine the behavior of households (e.g. occupational choices) based on characteristics of individuals from the household survey.[101] This approach can capture changes in population structure and employment shifts among sectors by using appropriate weighting. These models estimate econometrically the probability for household members to be in a certain labor market, derived from implicit utility functions and do not identify a particular labor market choice for each individual, but generate a probability distribution over the labor market choices of the population.[101] Some constraints have to be imposed to maintain consistency between the CGE and the microsimulation models with respect to total employment, wage rates and income levels.[99] This is usually done by adjusting the parameterization of the CGE model aiming to minimize the differences between the model results, while alternative approaches have been also analyzed.[99]

Although most applications of this approach are performed with static CGE models, attempts exist to use dynamic CGE models. Buddelmeyer et al.[102] combine a dynamic CGE model for Australia with a Micro-Simulation model, with both models using a similar population structure. The CGE model results are downscaled to the level of households (through Micro-Simulation modeling) and reweighted for structural changes in the population. The GTAP poverty framework (GTAP-Pov) is a microsimulation model drawing on national household survey data, sequentially linked to a “standard” GTAP CGE model,[103,104] used to perform policy analysis for single countries.

Data requirements include information on taxes, social benefits, hours worked, as well as information on the benefits system to determine implications of changes in a household earning for tax payments and/or eligibility for benefits. Behavioral microsimulation is more data-intensive since it needs background data that characterize

*“This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Grant Agreement No **730403**“*

household members to define behavioral choice modeling. To model occupational choices of households, information on household characteristics is required, e.g. age, gender, education, skills, children under six, etc.

In modeling approaches not including behavioral aspects, the changes in economic variables (i.e. employment, consumption) are determined by the survey data and the aggregate changes in the representative households (modeled with CGE). Therefore, this method cannot capture the characteristics of the individual households.[102] However, the inclusion of behavioral aspects may overcome these limitations and help the analysis of household economic behavior such as consumption preferences.

1.5.1.2 *Iterative Approach*

The iterative approach ensures that the information from micro-simulation models is fed back to the CGE or energy system models aiming to converge to a common solution in a few iterative steps. In the case of CGEs, the variables iterated across models are changes in employment, labour supply, wages, consumption patterns and prices.[98] In [105] the CGE determines and passes the prices, household income, goods supply and labour demand on to the micro-simulation model, which in turn calculates endogenously household incomes, consumption, labour supply and unemployment. Labour supply and consumption patterns change in both models as households respond to changes in wage rates, with the loop continuing until the models converge on consumption and labour supply.

Böhringer et al.[106] coupled a CGE model with a microsimulation model to assess the impacts of a green tax reform where additional revenues are redistributed lump-sum to Spanish households on an equal-per-capita basis. The quantitative evidence from coupled CGE and microsimulation analyses showed that such a green tax reform leads to a substantial reduction in harmful emissions while having a progressive impact on low-income households.

The way of modeling feedback from the micro-simulation to the CGE or energy system model influences the results of the approach. Results can also be affected by observed inconsistencies between the data from household surveys and the SAM used in CGE modelling or energy demand disaggregation in the energy system model. This can be prevented by adjusting either the micro or the macro data, at the stage of model development.

Rutherford et al.[107] showed that under some conditions (i.e. households not changing occupation) the iterative micro-simulation method resembles the same results as a multiple households CGE model. The combined CGE–Micro Simulation approach has the advantage of numerical tractability and reduced running time with respect to large numbers of households in income-expenditure surveys.[106]

1.5.1.3 *Hybrid Approach*

Hybrid approaches have also been developed, the most common of which is the combination of a multiple household CGE (representing a small number of household types) with direct modeling of the income distribution and micro-simulation to produce

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

results for a larger number of household types. This approach captures the general equilibrium effects (related to changes in prices, demand) between a large number of household categories within the CGE modeling framework.[74,108,109]

The hybrid approaches are even more data-intensive as they require (in addition to full-scale SAM) surveys with household-level data on 1) expenditures on goods, 2) wages and capital income 3) assets and demographic projection on changes in household characteristics, but also household-level information on taxes paid, social benefits and labor.

1.5.2 Integrated solutions with partial equilibrium

Partial equilibrium models are well-equipped as part of a suite of integrated solutions to assess the distributional impacts of energy and climate policies. The focus of partial equilibrium models is on the techno-economic pathways, which can include linking to other models or applying the equity evaluation.

As described in Section 4.1 and shown in Table 1, there are three variations to link models: coupling, soft-linking and hard-linking - each with its own advantages and disadvantages. The advantage of model linking methods is to retain a high level of detail in each of the separate models - similarly to disaggregation - and at the same time to maintain the flexibility of the different modeling frameworks. Retaining the positive aspects of the partial equilibrium framework to assess the long-term implications for energy transitions requires preserving the main method such that the soft-linking approach is most common. Capros et al.[110] applied the PRIMES model to quantify the impacts of the European “Clean Energy for all Europeans” package. The PRIMES model links a suite of detailed sector models, which although did not specifically aim to address distributional impacts, identifies specific challenges that not only impact the policy objectives but will have effects to consumers in terms of benefits and economic repercussions.

Fell et al.[15] reviewed integrated ways to capture the distributional impacts of long-term transitions by linking a partial equilibrium model with a higher level of disaggregation in the household sector with a model specifically designed to evaluate distributional impacts. This mixed-methods approach, however, allows to identify potential areas in long-term policies that might be of concern with regard to distributional impacts. Pye et al.[34] apply an equity evaluation as a means of linking information from different sources and models without changing the structure of each method.

The linked model approach of partial equilibrium with other models, such as macroeconomic models, is a powerful tool that offers a unique insight through the combination of long-term energy and climate policy pathways in conjunction with a view on their potential distributional impacts on specific groups. Soft-linking allows each model to maintain its framework and strengths without the burden of increasing the computational time or the model complexity.

1.6 Summary and Outlook

In this work, we reviewed several modeling frameworks that are i) commonly utilized for energy and environmental policy analysis and ii) capable of assessing the distributional impacts of such policies. This study comes from the necessity to better

*“This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Grant Agreement No **730403**“*

contemplate the distributional aspects of measures that aim at decreasing GHG emissions. This need is clearly stated at the 2030 Agenda for Sustainable Development signed by the United Nations Member States and is reflected on protests against fiscal policies that, despite aimed at curbing emissions, end up impacting low-income earners as it happened in Yellow vest movement.

Distributional effects refer to how the gains and costs of a project or policy are distributed among its participants, which in terms of policy-making may refer to different regions, sectors and households. This work focuses on the last dimension and examples of distributional effects, in this case, are the incidence of taxes, income growth, energy consumption and health damages caused by environmentally harming activities.

A number of modeling frameworks capable of depicting distributional impacts in different dimensions is presented, ranging from earlier methods such as energy and input-output models to more recent environmental impact assessment tools. The fundamentals of each framework are briefly described to provide a complete view of the diversity of modeling tools available for energy and environmental policy analysis.

Following, in Section 4 we discussed three individual modeling techniques with distinct focusses and how they incorporate distributional impacts into their analyses. First, energy system models using partial equilibrium formulation can be used to assess the technological requirements and costs of energy and environmental policies due to their high level of technical detail. However, the lack of feedback with other economic sectors constrains their use in climate policy analysis. Next, we move to general equilibrium models which are capable of accounting for feedback effects between sectors and regions in exchange for a less detailed technical description of the energy system. Finally, environmental impacts assessment models make it possible to estimate the health impacts of air pollution from fossil fuel consumption for energy-related activities.

Integrated solutions that involve linking two or more models in a single unified framework are reviewed in Section 5. We mainly discuss the combination of macroeconomic with micro-simulation models and integrated solutions involving partial equilibrium models because these are widely used to better represent distributional effects.

Among the techniques discussed in Sections 4 and 5, it is clear that a common solution for the inclusion of distributional effects on modeling frameworks is the disaggregation of sectors or households. The main challenge of this approach is the availability of data because it requires describing each individual representative household with specific information depending on the modeling framework being used. Therefore, the scarcity of data and difficult access to household surveys are obstacles that should be tackled to improve the analyses of distributional impacts of energy and environmental policies, especially those conducted by governments, which should in theory have easier access to these resources.

Integrated solutions offer a pathway to reconcile the strengths of different modeling approaches, but literature is scarce on linking different model types in a unified framework and also consider different household groups. In such a modeling exercise, data requirements are very high and there is also the issue of how the different models communicate with each other. In this case, one viable option is to select one central model that receives input from the others and reacts accordingly, such as the PRIMES or PROMETHEUS model,[14,111] with the addition of multiple representative households from section 4.2 or an integrated micro-simulation. Also, starting with static analysis of

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

a single region would help obtain useful insights for expanding the framework in future exercises.

Acknowledgements

The research leading to this study has received funding from the European Union Horizon 2020 research and innovation program under grant agreement No 730403 (INNOPATHS).

References

[1] E. Salies, OFCE Blog 2019.
[2] European Commission, European Semester Thematic Factsheet - Addressing Inequalities - 2017, n.d.
[3] D. Hardoon, S. Ayele, R. Fuentes-Nieva, Oxfam International, An Economy for the 1 %: How Privilege and Power in the Economy Drive Extreme Inequality and How This Can Be Stopped, Oxfam International, S.L., 2016.
[4] United Nations Development Programme, "Goal 10: Reduced inequalities," can be found under http://www.undp.org/content/seoul_policy_center/en/home/sustainable-development-goals/goal-10-reduced-inequalities.html, n.d.
[5] OECD, The Distributional Effects of Environmental Policy, OECD, 2006.
[6] N. Ohlendorf, M. Jakob, J. C. Minx, C. Schröder, J. C. Steckel, Distributional Impacts of Climate Mitigation Policies: A Meta-Analysis, Deutsches Institut Für Wirtschaftsforschung (DIW), Berlin, 2018.
[7] G. Zachmann, G. Fredriksson, G. Claeys, The Distributional Effects of Climate Policies, Brüssel, 2018.
[8] OECD, The Distributional Aspects of Environmental Quality and Environmental Policies: Opportunities for Individuals and Households, 2019.
[9] GBD 2017 Risk Factor Collaborators, The Lancet 2018, 392, 1923–1994.
[10] M. Zimmermann, S. Pye, Energy Policy 2018, 123, 594–601.
[11] European Commission, others, SEC 2009 2009, 92, 15.
[12] M. Grubb, J. Edmonds, P. ten Brink, M. Morrison, Annu. Rev. Energy Environ. 1993, 18, 397–478.
[13] R. Loulou, U. Remme, A. Kanudia, A. Lehtila, G. Goldstein, 2016.
[14] P. Fragkos, N. Tasios, L. Paroussos, P. Capros, S. Tsani, Energy Policy 2017, 100, 216–226.
[15] M. J. Fell, S. Pye, I. Hamilton, Environ. Innov. Soc. Transit. 2020, 35, 346–356.
[16] K. Hassett, A. Mathur, G. Metcalf, The Incidence of a U.S. Carbon Tax: A Lifetime and Regional Analysis, National Bureau Of Economic Research, Inc, 2007.
[17] K. Feng, K. Hubacek, D. Guan, M. Contestabile, J. Minx, J. Barrett, Environ. Sci. Technol. 2010, 44, 3670–3676.
[18] R. Anand, D. Coady, A. Mohommad, V. V. Thakoor, J. P. Walsh, The Fiscal and Welfare Impacts of Reforming Fuel Subsidies in India, International Monetary Fund, 2013.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

[19] K. Feng, K. Hubacek, Y. Liu, E. Marchán, A. Vogt-Schilb, Appl. Energy 2018, 225, 424–436.
[20] P. Bickel, R. Friedrich, Eds. , ExternE - Externalities of Energy: Methodology 2005 Update, Office For Official Publications Of The European Communities, Luxembourg, 2005.
[21] A. Deaton, J. Muellbauer, Am. Econ. Rev. 1980, 70, 312–26.
[22] S. E. West, R. C. W. III, Estimates from a Consumer Demand System: Implications for the Incidence of Environmental Taxes, National Bureau Of Economic Research, Inc, 2002.
[23] J. A. Rosas-Flores, M. Bakhat, D. Rosas-Flores, J. L. Fernández Zayas, Energy Econ. 2017, 61, 21–28.
[24] J. Banks, R. Blundell, A. Lewbel, Rev. Econ. Stat. 1997, 79, 527–539.
[25] R. Brännlund, J. Nordström, Eur. Econ. Rev. 2004, 48, 211–233.
[26] D. Nikodinoska, C. Schröder, Resour. Energy Econ. 2016, 44, 206–233.
[27] A. Lewbel, K. Pendakur, Tricks With Hicks: The EASI Demand System, Boston College Department Of Economics, 2006.
[28] M. A. Tovar Reaños, N. M. Wölfing, Energy Econ. 2018, 70, 84–97.
[29] A. Berry, Energy Policy 2019, 124, 81–94.
[30] B. J. van Ruijven, B. C. O'Neill, J. Chateau, Energy Econ. 2015, 51, 530–543.
[31] J. W. Bae, E. Paik, K. Kim, K. Singh, M. Sajjad, Procedia Comput. Sci. 2016, 80, 507–517.
[32] X. Labandeira, J. M. Labeaga, M. Rodríguez, Energy Policy 2009, 37, 5776–5786.
[33] N. Sabio, S. Pye, N. Strachan, 2014.
[34] S. Pye, A. Dobbins, M. Matosović, V. Lekavičius, 2019, DOI 10.5281/zenodo.3368507.
[35] V. Alexeeva-Talebi, C. Böhringer, A. Löschel, S. Voigt, Energy Econ. 2012, 34, S127–S142.
[36] J. Tomaschek, A. Dobbins, U. Fahl, Cape Town, 2012.
[37] A. Dobbins, U. Fahl, K. Hufendiek, University College London, 2015.
[38] J.-M. Cayla, N. Maïzi, Appl. Energy 2015, 139, 56–67.
[39] A.H. Dobbins, The Significance of Energy Poverty and Low Income as Key Barriers to the Achievement of Household Energy and Emissions Targets in Germany, Doctoral, University of Stuttgart, Institute of Energy economics and Rational energy use (IER), In preparation.
[40] T. Fotiou, A. de Vita, P. Capros, Energies 2019, 12, 2745.
[41] B. Doda, S. Fankhauser, Energy Policy 2020, 138, 111205.
[42] C.-O. Wene, Energy 1996, 21, 809–824.
[43] A. J. Chapman, N. A. Pambudi, J. Clean. Prod. 2018, 172, 1014–1024.
[44] I. Teichmann, CGE-Based Methods to Measure the Impact of Trade Liberalization on Poverty, Deutsches Institut Für Wirtschaftsforschung (DIW), Berlin, 2016.
[45] I. Adelman, S. Robinson, Income Distrtibution Policy in Developing Countries: A Case Study of Korea, Published For The World Bank [By] Oxford University Press, Oxford ; New York, 1978.
[46] M. Dalton, B. O'Neill, A. Prskawetz, L. Jiang, J. Pitkin, Energy Econ. 2008, 30, 642–675.
[47] N. B. Melnikov, B. C. O'Neill, M. G. Dalton, Energy Econ. 2012, 34, 1475–1483.
[48] B. C. O'Neill, M. Dalton, R. Fuchs, L. Jiang, S. Pachauri, K. Zigova, Proc. Natl. Acad. Sci. 2010, 107, 17521–17526.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

[49] A. Bouet, C. Estrades, D. Laborde, Households Heterogeneity in a Global CGE Model: An Illustration with the MIRAGE-HH (MIRAGE-HouseHolds) Model, 2013.
[50] T. W. Hertel, M. B. Burke, D. B. Lobell, Glob. Environ. Change 2010, 20, 577–585.
[51] V. Ahmed, C. O' Donoghue, CGE-Microsimulation Modelling: A Survey, University Library Of Munich, Germany, 2007.
[52] F. Bourguignon, M. Bussolo, in Handb. Comput. Gen. Equilib. Model. (Eds.: P.B. Dixon, D.W. Jorgenson), Elsevier, 2013, pp. 1383–1437.
[53] N. B. Melnikov, B. C. O'Neill, M. G. Dalton, B. J. van Ruijven, Energy Econ. 2017, 65, 87–97.
[54] D. Boccanfuso, B. Decaluwé, L. Savard, J. Econ. Inequal. 2008, 6, 149–184.
[55] D. van der Mensbrugghe, "Shared Socio-economic pathways and global income distribution," can be found under http://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=4790, 2015.
[56] L. Groot, T. Oostveen, Rev. Dev. Econ. 2019, 23, 1926–1944.
[57] A. Orlov, Energy Policy 2017, 109, 590–600.
[58] R. Cunha Montenegro, V. Lekavičius, J. Brajković, U. Fahl, K. Hufendiek, Sustainability 2019, 11, 6868.
[59] S. Rausch, G. Metcalf, J. Reilly, Distributional Impacts of Carbon Pricing: A General Equilibrium Approach with Micro-Data for Households, National Bureau Of Economic Research, Cambridge, MA, 2011.
[60] W. W. Leontief, Rev. Econ. Stat. 1936, 18, 105–125.
[61] "Input-Output Tables (IOTs) - OECD," can be found under http://www.oecd.org/sti/ind/input-outputtables.htm, n.d.
[62] Y. Wang, J. Li, L.-C. Lee, M. Wang, H. Du, Environ. Rev. 2019, 27, 567–574.
[63] C. Grainger, A. Schreiber, F. Zhang, Energy Policy 2019, 125, 65–81.
[64] H. Zhang, G. J. D. Hewings, X. Zheng, Energy Policy 2019, 128, 223–234.
[65] M. L. Cloutier, P. J. Thomassin, Econ. Syst. Res. 1994, 6, 397–414.
[66] K. Miyazawa, in Input-Output Anal. Struct. Income Distrib., Springer Berlin Heidelberg, Berlin, Heidelberg, 1976, pp. 22–42.
[67] C. Ramos Carvajal, A. S. García-Muñiz, B. Moreno Cuartas, Energies 2019, 12, 4486.
[68] P. Mohai, D. Pellow, J. T. Roberts, Annu. Rev. Environ. Resour. 2009, 34, 405–430.
[69] A. Hajat, C. Hsia, M. S. O'Neill, Curr. Environ. Health Rep. 2015, 2, 440–450.
[70] O. Laurent, D. Bard, L. Filleul, C. Segala, J. Epidemiol. Amp Community Health 2007, 61, 665–675.
[71] W. Bowen, Environ. Manage. 2002, 29, 3–15.
[72] IPCC, Climate Change 2014 Impacts, Adaptation, and Vulnerability: Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, 2014.
[73] A. Kitous, K. Keramidas, T. Vandyck, B. Saveyn, R. Van Dingenen, J. V. Spadaro, M. Holland, Europäische Kommission, Gemeinsame Forschungsstelle, How Climate Policies Improve Air Quality: Global Energy Trends and Ancillary Benefits of the Paris Agreement, 2017.
[74] T. Vandyck, D. Van Regemorter, Energy Policy 2014, 72, 190–203.
[75] European Commission, In-Depth Analysis in Support of the Commission Communication COM(2018) 773: A Clean Planet for All - A European Long-Term

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Strategic Vision for a Prosperous, Modern, Competitive and Climate Neutral Economy, 2018.
[76] G. Kiesewetter, J. Borken-Kleefeld, W. Schöpp, C. Heyes, P. Thunis, B. Bessagnet, E. Terrenoire, A. Gsella, M. Amann, Atmospheric Chem. Phys. 2014, 14, 813–829.
[77] G. Kiesewetter, W. Schoepp, C. Heyes, M. Amann, Environ. Model. Softw. 2015, 74, 201–211.
[78] G. Kiesewetter, J. Borken-Kleefeld, W. Schöpp, C. Heyes, P. Thunis, B. Bessagnet, E. Terrenoire, H. Fagerli, A. Nyiri, M. Amann, Atmospheric Chem. Phys. 2015, 15, 1539–1553.
[79] P. Thunis, B. Degraeuwe, E. Pisoni, F. Ferrari, A. Clappier, J. Environ. Manage. 2016, 183, 952–958.
[80] P. Thunis, B. Degraeuwe, E. Pisoni, M. Trombetti, E. Peduzzi, C. A. Belis, J. Wilson, A. Clappier, E. Vignati, Atmos. Environ. 2018, 187, 93–106.
[81] E. Pisoni, P. Thunis, A. Clappier, Atmospheric Environ. X 2019, 4, 100047.
[82] E. Pisoni, P. Christidis, P. Thunis, M. Trombetti, J. Environ. Manage. 2019, 231, 249–255.
[83] M. Ravina, D. Panepinto, M. C. Zanetti, Atmos. Environ. 2018, 173, 81–95.
[84] M. Ravina, D. Panepinto, M. C. Zanetti, G. Genon, Environ. Sci. Pollut. Res. 2017, 24, 13424–13436.
[85] A. Gens, J. F. Hurley, J. T. Tuomisto, R. Friedrich, Atmos. Environ. 2014, 84, 213–221.
[86] N. Li, C. N. Maesano, R. Friedrich, E. Medda, S. Brandstetter, M. Kabesch, C. Apfelbacher, M. Melter, B. Seelbach-Göbel, I. Annesi-Maesano, D. Sarigiannis, Environ. Res. 2019, 178, 108629.
[87] N. Li, R. Friedrich, C. N. Maesano, E. Medda, S. Brescianini, M. A. Stazi, C. E. Sabel, D. Sarigiannis, I. Annesi-Maesano, Environ. Res. 2019, 179, 108744.
[88] J. V. Zidek, G. Shaddick, R. White, J. Meloche, C. Chatfield, Environmetrics 2005, 16, 481–493.
[89] N. Li, R. Friedrich, Atmosphere 2019, 10, 507.
[90] A. Gens, 2012, DOI 10.18419/OPUS-2021.
[91] L. E. Gerharz, A. Krüger, O. Klemm, Sci. Total Environ. 2009, 407, 5184–5193.
[92] S. Vallamsundar, J. Lin, K. Konduri, X. Zhou, R. M. Pendyala, Transp. Res. Part Transp. Environ. 2016, 46, 94–113.
[93] D. Chapizanis, S. Karakitsios, A. Gotti, D. A. Sarigiannis, Environ. Res. 2021, 192, 110141.
[94] L. Yang, P. Hoffmann, J. Scheffran, S. Rühe, J. Fischereit, I. Gasser, Urban Sci. 2018, 2, 36.
[95] D. Chapizanis, S. Karakitsios, D. A. Sarigiannis, ISEE Conf. Abstr. 2018, 2018, isesisee.2018.S02.02.23.
[96] D. Schmid, P. Korkmaz, M. Blesl, U. Fahl, R. Friedrich, Energy Strategy Rev. 2019, 26, 100417.
[97] P. Korkmaz, R. Cunha Montenegro, D. Schmid, M. Blesl, U. Fahl, Energies 2020, 13, 707.
[98] G. Colombo, Int. J. Microsimulation 2010, 3, 72–91.
[99] N. Herault, Int. J. Microsimulation 2010, 3, 35–42.
[100] J. Lay, Int. J. Microsimulation 2010, 3, 24–34.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

[101] F. Bourguignon, A.-S. Robilliard, S. Robinson, in Front. Appl. Gen. Equilib. Model. Honor Herbert Scarf (Eds.: J. Whalley, T.N. Srinivasan, T.J. Kehoe), Cambridge University Press, Cambridge, 2005, pp. 219–254.
[102] H. Buddelmeyer, N. Herault, G. Kalb, M. V. Z. D. Jong, 2008.
[103] S. A. Ahmed, N. S. Diffenbaugh, T. W. Hertel, D. B. Lobell, N. Ramankutty, A. R. Rios, P. Rowhani, Glob. Environ. Change 2011, 21, 46–55.
[104] T. Hertel, M. Verma, M. Ivanic, E. Magalhaes, C. Ludena, A. R. Rios, "GTAP-POV: A Framework for Assessing the National Poverty Impacts of Global Economic and Environmental Policies," can be found under http://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=3731, 2011.
[105] L. Savard, Poverty and Income Distribution in a Cge-Household Micro-Simulation Model: Top-Down/Bottom Up Approach, Social Science Research Network, Rochester, NY, 2003.
[106] C. Böhringer, X. Garcia-Muros, M. González-Eguino, Greener and Fairer: A Progressive Environmental Tax Reform for Spain, Oldenburg Discussion Papers In Economics, 2019.
[107] T. Rutherford, D. Tarr, O. Shepotylo, 2005, DOI 10.1596/1813-9450-3725.
[108] I. Coxhead, A. Wattanakuljarus, C. V. Nguyen, World Dev. 2013, 51, 119–131
[109] G. Verikios, X. Zhang, Econ. Model. 2015, 44, 7–17.
[110] P. Capros, M. Kannavou, S. Evangelopoulou, A. Petropoulos, P. Siskos, N. Tasios, G. Zazias, A. DeVita, Energy Strategy Rev. 2018, 22, 255–263.
[111] P. Fragkos, N. Kouvaritakis, Energy 2018, 160, 965–978.
[112] L. Mathiesen, in Econ. Equilib. Model Formul. Solut. (Eds.: R.W. Cottle, L.C.W. Dixon, B. Korte, M.J. Todd, E.L. Allgower, W.H. Cunningham, J.E. Dennis, B.C. Eaves, R. Fletcher, D. Goldfarb, J.-B. Hiriart-Urruty, M. Iri, R.G. Jeroslow, D.S. Johnson, C. Lemarechal, L. Lovasz, L. McLinden, M.J.D. Powell, W.R. Pulleyblank, A.H.G. Rinnooy Kan, K. Ritter, R.W.H. Sargent, D.F. Shanno, L.E. Trotter, H. Tuy, R.J.B. Wets, E.M.L. Beale, G.B. Dantzig, L.V. Kantorovich, T.C. Koopmans, A.W. Tucker, P. Wolfe, A.S. Manne), Springer Berlin Heidelberg, Berlin, Heidelberg, 1985, pp. 144–162.

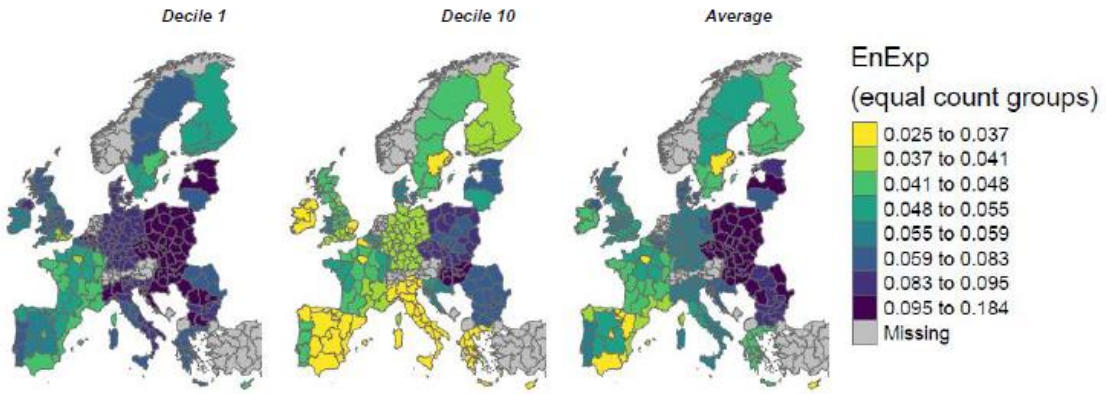


Figure 1. Average household expenditure on energy by income decile (lowest, highest and average) by NUTS1 regions across Europe.[31] CC BY 4.0

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

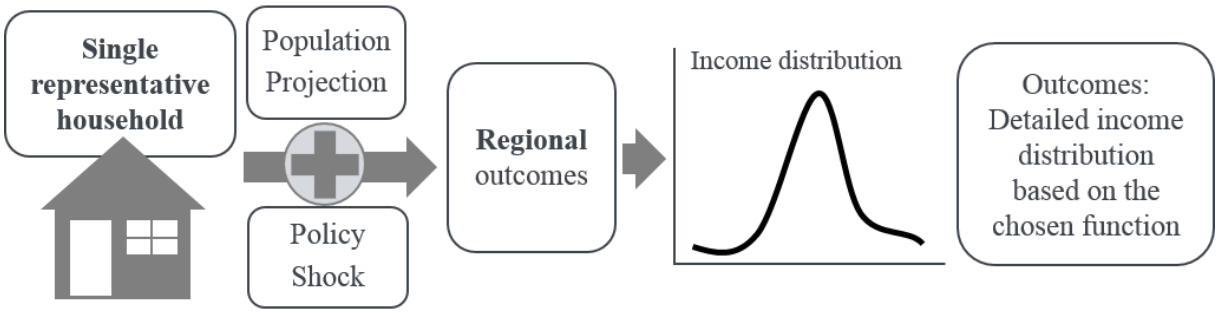


Figure 2. Schematic representation of direct modeling of income distribution. By the authors.

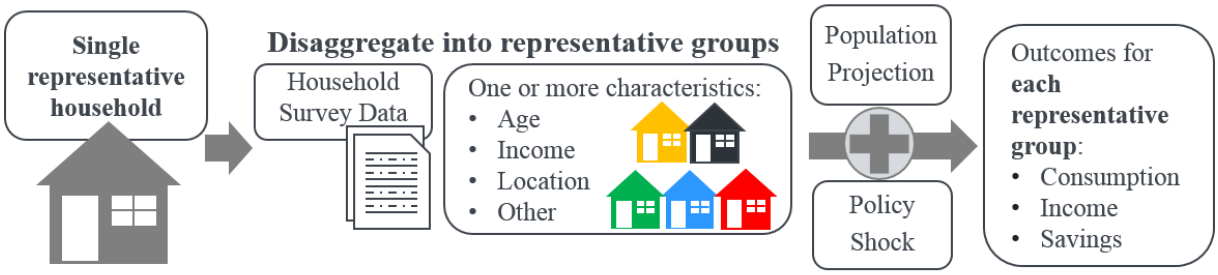


Figure 3. Schematic representation of the approach with multiple households. By the authors.

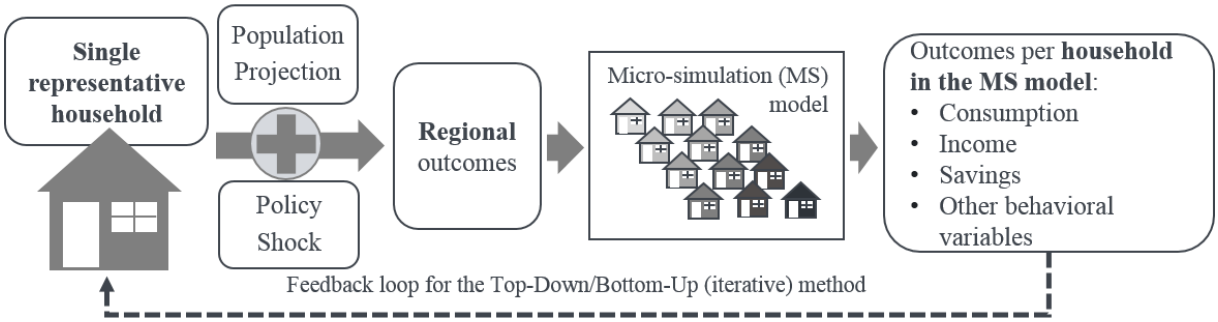


Figure 4. Schematic representation of the approach with micro-simulation. By the authors.

Table 1. Comparison of common modeling approaches to assess distributional impacts in partial equilibrium energy system models

Method	Strengths	Weaknesses
Model disaggregation	Allows greater detail in representative groups; Explicitly defines and considers particular socio-economic	Data-intensive, data availability, long-term data projections, model complexity and run-time increased

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

		groups according to their specific circumstances	
Linking sector models	***Coupling***	Requires moderate skill level and less detailed knowledge of separate models; Model algorithms and formulation remain unchanged	Direct link between the models needed via variables; Iterations may result in higher computational times and prove more arduous depending on the number of variables exchanged
	Soft-linking	Requires moderate skill level and intermediate model knowledge; Model algorithms and formulation remain unchanged; Makes use of the tool's capabilities	Data analysis is intensive to determine the level of harmonization required. Medium tool development time.
	Hard-linking	Requires high skill level and knowledge of model; Model reformulation required (and development of new source code) Full exploitation of tool strengths	Intensive model analysis and harmonization High tool development time All possible communication channels need to be joined and harmonized.
Equity evaluation		A flexible framework, which allows all other models used to maintain their structure	Data and assumptions can be intensive or scarce Does not capture the complex interlinkages among actors and sectors, such as in the hard-linking method

Supporting Information

Equation S1

$$Total\ discounted\ system\ costs = \sum_{r=1}^{R} \sum_{y \in YEARS} (1 + d_{r,y})^{REFYR-y} \times ANNCOST(r,y)$$

Where:

R	is the set of regions in the area of study;
$YEARS$	is the set of total milestone years in the modelling horizon;
$REFYR$	is the reference year to which all costs/revenues are discounted;
$d_{r,y}$	is the global discount rate (in this study fixed across regions and years);

"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"

$ANNCOST(r,y)$ is the total annual cost in region r and year y.

Mathematical description of the CGE model

Although exhibiting great variety, CGE models tend to share various characteristics. Below we describe a common core of features which most CGE models share. CGE models focus on the production of commodities by industries distinguishing various production sectors. The commodities are demanded by industries and by final demanders (household, investment, government and rest of world). Income arising from primary factor rents and from taxes and transfers is distributed to (and drives spending by) "agents" such as households, corporations, government and rest of world.

Industry input demands are usually assumed to be proportional to output (constant-returns to scale) and sensitive to relative prices. The industry demand functions assume that production (output) is a function of input quantities and producers choose the cheapest combination of inputs that will produce a given output. For example, if an industry has multiple inputs, we may stipulate an activity index Z=F(inputs), such that the sector will choose the cost-minimizing mix of inputs to produce Z. Very often the F function is separable, i.e. :

$$F(inputs) = H\ (I(primary\ factors), J(material\ inputs))$$

Similarly, an industry's choice of how much inputs will use is modelled independently of the choice whether to use domestically produced or imported inputs. Household, government and investment demands are modeled in a similar way. Thus, complicated demand systems are built up from a series of demand functions, which

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

usually take the form of CES type. The remaining core equations of the typical CGE model are fairly simple, consisting of:

- Market-clearing equations that add up total demands for each good and, for domestic goods equate demand to domestic output.
- Price equations that relate tax-inclusive user prices to output or c.i.f. (cost, insurance and freight) prices.
- Income equations that add up total revenue accruing to each agent

Usually one (or a small number) of behavioral specifications is applied to all sectors, households or regions. That is, the same functional form is used for all, say, industry demand equations. Differences between goods or household types are captured with good-or household-specific numbers held on or deducible from the model database.

An economic equilibrium can be cast as a mixed complementarity problem. For illustration, we consider a standard Arrow-Debreu economy with n commodities (incl. factors), m sectors and households (incl. government). The endogenous variables of the Arrow-Debreu economy can be classified into 3 categories[112]:

p: a non-negative n-vector in prices for all goods and factors (I ={1,...,n}),

y: a non-negative m-vector for activity levels of CRTS-production sectors (J={1,...,M}),

M: a non-negative k-vector in incomes (H ={1,...,k}).

In equilibrium the variables must fulfill three classes of conditions:

- Zero profit of CRTS-producers (exhaustion-of-product constraint)

Equation S2

$-\Pi_j(p) = C_j(p) - R_j(p) \geq 0$ for all j

Where using Hotelling's Lemma:

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

$\Pi_j(p)$ the unit profit function

$C_j(p) \equiv min\left\{\sum_i p_i \frac{\partial \Pi_j}{\partial p_i} \middle| f_j(.) = 1\right\}$ the unit cost function and

$R_j(p) \equiv max\left\{\sum_i p_i \frac{\partial \Pi_j}{\partial p_i} \middle| g_j(.) = 1\right\}$ the unit revenue function

The functions f_j and g_j characterize feasible input- and output-combinations of production in

sector j.

- Market clearance for all goods and factors:

Equation S3

$\sum_j y_j \frac{\partial \Pi_j(p)}{\partial p_i} + \sum_h b_{i,h} \geq \sum_h d_{i,h}$ for all I, where

$b_{i,h}$ the initial endowment of household h with commodity i and

$d_{i,h}(p, M_h) \equiv argmax\{U_h(x) | \sum_i p_i x_i = M_h\}$ the demand for good i by household h

maximizing utility (U_h denotes the utility function of household h)

- Budget constraints for households:

Equation S4

$\sum_h p_i b_{i,h} = M_h \geq \sum_h p_i d_{i,h} \, for\ all\ h$

For common utility functions (non-satiation), households are always on their budget

line, i.e.

$\sum_h p_i b_{i,h} = M_h = \sum_h p_i d_{i,h}$ and Walras' law holds

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Research paper 2: Is time preference different across incomes and countries

Vincenzo De Lipsis, UCL

Status of the research paper: *The paper has been submitted for review in the Economics Letters scientific journal*

Abstract:

We offer direct statistical evidence of existing differences in time preference across income classes and countries by estimating and testing an Euler equation for consumption on time series data for six European countries and five income quantiles. We unequivocally reject the hypothesis of homogeneous time preference across countries, whereas heterogeneity across income classes is confirmed to different degrees depending on the country, but with time preference being lowest for the last two quantiles of the income distribution

Keywords: Time preference, discount rate, Euler equation, GMM testing.

Acknowledgement: This work is part of the INNOPATHS research project, funded by the European Union Horizon 2020 Research and Innovation Programme under Grant Agreement No: 730403.

2.1 Introduction

The subjective discount rate is a fundamental parameter in any economic model that describes problems of intertemporal allocation of resources, consumption or capital. It is also well-known that the degree with which individuals discount the future is a function of a large list of factors, starting with income, wealth, education and culture. This explains at least in part why empirical evidence and experimental procedures to estimate the time preference have delivered an incredibly wide range of values (Frederick et al. 2002).

The idea that the income level is important for the determination of time preference has received empirical support since the work of Hausman (1979), who finds a strong inverse relation from individual consumption choices related to energy efficient appliances, while the policy relevance of time preference heterogeneity has been highlighted by Samwick (1998). Lawrance (1991) explores the influence of income, age, education and race on time preference, highlighting in particular that the discount rate of poorer families are higher than that of richer ones by up to five percentage points, though results are not always in the same direction (e.g. Ogaki and Atkenson, 1997).

The inverse relation between time preference and income level is explained by Lawrance (1991) as a result of imperfect capital markets that prevent impatient individuals from investing in education, but also by appealing to more deep-seated cultural factors. This latter dimension has been investigated only recently, for instance by Wang et al. (2016), who use hypothetical questions to elicit time preferences across a sample of 53 countries, finding that culture accounts for a large amount of observed variation in the discount rate, and by Falk et al. (2018), who construct a large dataset from a global survey over 76 countries revealing strong heterogeneity in time preference that is related to geography and culture.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

We offer new evidence on the relation between time preference on one side and income and culture on the other, by estimating discount rates for a set of six European countries and for five different income classes using time series data and calculating an explicit test of these differences. Estimation benefits from the use of a carefully-designed data driven procedure to select the GMM instruments, which are then combined together in a system GMM estimation that allows a direct test of our hypothesis. We find that there is overwhelming evidence of differences in time preference between countries conditional on the same income class, and a more varied picture as to the within-country differences across income classes, but an overall confirmation that the discount rate is lowest for high-income individuals.

2.2 Method

To estimate the discount rate, we make use of a standard formulation of the Euler equation resulting from the intertemporal optimization problem of the consumer under the hypothesis of rational expectations. We assume the utility function has a standard CRRA form

$$U(C_t) = \frac{C_t^{1-\gamma}}{1-\gamma}, \tag{1}$$

from which the intertemporal FOC follows as

$$E\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\frac{(1+R_{t+1})}{(1+\rho)}\right] = 1, \tag{2}$$

where C_t is the individual consumption at time t, γ is the coefficient of relative risk aversion, R_{t+1} is the nominal interest rate across the two periods, ρ is the discount rate, and E[·] is the expectation conditional on the information set at time t.

Estimation of model (2) is conducted using GMM on time series data, in a tradition started with Hansen and Singleton (1982). Pros and cons of a time series approach as opposed to a panel data analysis at household level are well-known, but it is worth stressing one main advantage of the first approach over the second, consisting in the opportunity to exploit a long horizon of co-movements in interest rate, prices and consumption, which is fundamental when the priority is to estimate the time preference rate[2].

We estimate model (2) using non-linear iterated GMM combined with the data-driven method to select the moment conditions suggested by Hall (2005). This method consists in the application of a two-step procedure: in the first step we minimize the "moment selection criterion" across all cumulative lag order for $\frac{C_{t+1}}{C_t}$and $1 + R_{t+1}$ up to lag 5; in the second step, we search, among all possible combinations of instruments

[2] Both empirical strategies in the case of nonlinear specifications suffer from measurement error problems; the time series approach is affected by aggregation bias, but its inference is more reliable if we consider that in the absence of complete capital markets shocks are likely to have cross-section correlation, which means that the asymptotic approximation has to rely on a large time dimension of the sample (Attanasio and Low 2004)

"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"

obtainable from the set selected in the first step, that specific one that minimizes the "relevant moment criterion"[3]. Although its application is rare, the value of this data-driven method stems from three main reasons: it avoids an arbitrary choice of the instruments, which is important as GMM estimates in general can be very sensitive to the instruments selection; it ensures that validity and relevance of the moment conditions are satisfied in practice; its good performance in finite samples has been shown in simulation studies (Hall and Peixe, 2003; Hall et al. 2007)[4].

After obtaining the estimates for the discount rate for different income classes and countries, we are interested in evaluating the statistical significance of any difference in value. In particular, we want to test two sets of hypotheses: first, the equality across income classes within each country; second, the equality across countries conditional on each income class. With this aim we set up a system in which we stack the moment conditions of the set of structural equations of interest using the instruments already selected in the single-equation estimation, and we implement a system version of the iterated GMM, from which we calculate the D test. We also report the result of the Wald test as an additional source of evidence but we give prominence the D test as this is known to perform better in finite samples and is invariant to the model parameterization.

As income dynamics are dominated by consumption choices at business cycle frequency and the consumption share is very stable over the period of our sample, we use the income data from the Global Consumption and Income Project (Lahoti et al. 2016), which consists in annual observations over the period 1960-2015 of the mean income per capita in 2005 constant prices, converted in 2005 PPP dollars, divided in 5 quintiles, for six European countries, namely France, Germany, Italy, Spain, Sweden and the UK[5]. For the interest rate we use the 3-month rate on Treasury bonds for each country, collected from the Main Economic Indicators of the OECD. Data limitation on this variable determines the effective time span used in estimation, which ranges from 37 of Italy to 56 of Germany. The price index is the CPI obtained from the International Financial Statistics of the IMF. The real interest rate is calculated by deflating the nominal interest rate by the increase in the annual average CPI.

2.3 Results

The results from the single-equation iterated GMM estimation with the data-driven selection of instruments are displayed in Table 1. In all 30 estimations we get strong statistical significance with virtually zero p values in most cases. As we can notice, the discount rate does not change monotonically across each income class, but for all countries except Italy the last two income quintiles are lower than the first three quintiles. In the case of France, Sweden and the UK, both the 4th and 5th quintiles are individually lower than the first three quintiles, while for Germany and Spain their average is. This

[3] With 5 lags and 2 variables, there are 961 possible sets of instruments with cardinality from 1 to 5.

[4] By contrast, the alternative strategy to aim for optimal instruments faces important obstacles in terms of feasibility, as economic theory does not provide enough basis for defining the assumptions needed on the data generating process, it does not help in making sure orthogonality holds, and its performance in finite sample is at least doubtful

[5] This dataset combines different existing datasets, such as the European Union Survey of Living conditions (EU-SILC), Luxembourg Income Study, UNU-WIDER World Income Inequality Database, and Branko Milanovics WYD database

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

outcome suggests that there is a common threshold in terms of income level above which time preference becomes markedly lower. This level of income appears very similar among France, Germany, Sweden, and UK as the mean income of the 4th quintile is around 18,000 in 2005, though substantially lower for Spain where it is roughly 13,000.

As the differences in estimates might reflect only sampling variability, we proceed in testing these differences. The first hypothesis under test is the equality across income classes within each country. First we assess the overall statistical difference across all income classes. Then, we consider two groups, the first three quintiles and the last two quintiles. We test the homogeneity within the groups, and if this is not rejected we also test the difference between groups. In practice, as the within group homogeneity is almost always rejected we do not proceed forward in testing the between group difference.

Table 1: Discount rate estimates

	Income quintile				
	1st	***2nd***	***3rd***	***4th***	***5th***
France	0.0163	0.0177	0.0190	0.0111	0.0124
Germany	0.0230	0.0237	0.0241	0.0232	0.0211
Italy	0.0272	0.0298	0.0245	0.0318	0.0254
Spain	0.0214	0.0160	0.0120	0.0067	0.0131
Sweden	0.0262	0.0279	0.0373	0.0081	0.0125
UK	0.0340	0.0250	0.0263	0.0246	0.0222

Note: All estimates are significant with pvalue < 0.01.

The outcome is shown in Table 2. In only one instance, Germany, the evidence unequivocally points to no statistical difference in the discount rate of different income classes. In all the other cases, the D test rejects the null, though this is not conclusive in the case of Italy and Sweden as the J test suggests at 5% the risk that misspecification might contaminate the result. In Spain result is strongest in rejecting the null as also the Wald test rejects with very small p-value. When we test the statistical difference within the two groups, the D test rejects all times with very small p-values, again with the exception of Germany.

Table 2: Equality across income classes

		all quintiles		within group	
	J	***D***	***W***	***D***	***W***
France	0.231	0.000	0.390	0.000	0.318
Germany	0.168	0.962	0.967	0.943	0.955
Italy	0.045	0.000	0.068	0.000	0.111
Spain	0.574	0.000	0.000	0.000	0.000
Sweden	0.004	0.000	0.456	0.000	0.309
UK	0.307	0.000	0.091	0.000	0.048

Note: J, D, and W are pvalues of respectively the J, D, and Wald test statistic.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

The second hypothesis under test is the equality across countries, conditional on a specific income class. We assess the overall statistical difference across all countries, and then we consider three geographically-determined groups: south (Italy, Spain), center (France, Germany), and north (Sweden, UK). We test the within group equality, and if not rejecting we move to testing the between group equality. As in practice we never fail to reject the within group equality, we do not end up performing the second test.

The outcome of this tests is displayed in Table 3. Here, unequivocally and strongly, whether using the D or the Wald tests, we reject the equality of discount rates across countries, for every income classes, with very small p-values and without the risk of contamination due to model misspecification. Finally, we also reject the within group equality in all income classes with very small p-values.

Table 3: Equality across countries

		All countries		within group	
Quintile	***J***	***D***	***W***	***D***	***W***
1st	0.113	0.000	0.000	0.000	0.000
2nd	0.179	0.000	0.000	0.000	0.000
3rd	0.283	0.000	0.000	0.000	0.000
4th	0.057	0.000	0.000	0.000	0.000
5th	0.189	0.000	0.001	0.000	0.044

Note: J, D, and W are pvalues of respectively the J, D, and Wald test statistic.

2.4 Conclusions

Theory predicts an important relationship between time preference on one side and income and country-specific factors on the other, and substantive amount of evidence has supported such hypothesis, though no attempt has been made in terms of directly testing the difference in time preference across income classes and countries. We performed such test using time series data on six European countries distinguishing five income classes. Results showed that discount rates does not decrease monotonically across income classes, but there is almost always a threshold level of income beyond which the discount rate is substantially smaller. We found that these differences are statistically significant, though with dissimilar degrees of strength depending on the country, whereas the differences in time preference between countries are unequivocally confirmed at all income levels, reflecting country-specific factors such as culture and institutions.

References

Attanasio, O.P. and Low, H., 2004. Estimating euler equations. Review of Economic Dynamics, 7(2), pp.406-435.

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D. and Sunde, U., 2018. Global evidence on economic preferences. The Quarterly Journal of Economics, 133(4), pp.1645- 1692.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Frederick, S., Loewenstein, G. and O'donoghue, T., 2002. Time discounting and time preference: A critical review. Journal of Economic Literature, 40(2), pp.351-401.

Hall, A.R., 2005. Generalized method of moments. Oxford university press.

Hall, A.R., Inoue, A., Jana, K. and Shin, C., 2007. Information in generalized method of moments estimation and entropy-based moment selection. Journal of Econometrics, 138(2), pp.488-512.

Hall, A.R. and Peixe, F.P., 2003. A consistent method for the selection of relevant instruments. Econometric reviews, 22(3), pp.269-287.

Hausman, J.A., 1979. Individual discount rates and the purchase and utilization of energyusing durables. The Bell Journal of Economics, pp.33-54.

Lahoti, R., Jayadev, A. and Reddy, S., 2016. The global consumption and income project (GCIP): An overview. Journal of Globalization and Development, 7(1), pp.61-108.

Lawrance, E.C., 1991. Poverty and the rate of time preference: evidence from panel data. Journal of Political Economy, 99(1), pp.54-77.

Ogaki, M. and Atkeson, A., 1997. Rate of time preference, intertemporal elasticity of substitution, and level of wealth. Review of Economics and Statistics, 79(4), pp.564-572.

Samwick, A.A., 1998. Discount rate heterogeneity and social security reform. Journal of Development Economics, 57(1), pp.117-146.

Hansen, L.P. and Singleton, K.J., 1982. Generalized instrumental variables estimation of nonlinear rational expectations models. Econometrica. Journal of the Econometric Society, pp.1269-1286.

Wang, M., Rieger, M.O. and Hens, T., 2016. How time preferences differ: Evidence from 53 countries. Journal of Economic Psychology, 52, pp.115-135.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Research paper 3: Distributional effects of a post-pandemic green fiscal stimulus: skills, employment and wage of low-skilled manual workers

Status of the research paper: *The paper is under review in the JEEM special issue on Coronavirus*

Marin, G., Vona, F., Popp, D., Chen, Z., 2020. 'Distributional effects of a post-pandemic green fiscal stimulus: skills, employment and wage of low-skilled manual workers,' under review JEEM special issue on Coronavirus.

Abstract:

A green fiscal stimulus is prominent in the policy debate over government investments to aid the recovery from the Covid-19 pandemic. Supporters argue green stimuli would boost GDP, create jobs and, at the same time, help redirect economic systems towards the strategic long-term goal of tackling the climatic crisis. In this paper we provide new evidence on the distance in worker skill sets between occupations displaced by Covid-19 and other structural shocks and the subset of green-manual occupations that are expected to be in high-demand as a consequence of a green stimulus. We show that skill distance and other barriers could limit a transition of displaced workers to green-manual jobs. However, our ex-post assessment of the green component of the American Recovery and Reinvestment Act of 2009 suggests that training programs may help. We show that areas equipped with green training facilities gain the most in terms of employment and wages for green-manual jobs after a green fiscal stimulus.

Keywords: green skills distance, green fiscal stimulus, Covid-19

JEL Codes: Q58, J24, H54

3.1 Introduction

Recovery from the Covid-19 pandemic will require a large government stimulus to help those companies and workers most affected by both the present and future lockdowns as well as by the structural changes that will follow. Besides obvious income effects, the Covid-19 crisis may induce permanent changes in the composition of demand such as a reduction of travelling, holidays, restaurants, and personal services. On the supply side, minimizing the impact of future social distancing restrictions on business may accelerate the rate of automation.

Investing in the green economy has been identified as a strategic area of intervention to jointly target the climate crisis and the economic crisis induced by the Covid-19 pandemic (e.g. Helm 2020; Agrawala et al., 2020). A leading example is the EU Recovery Plan for Europe (Next Generation EU, €750 billion for 2021-2027) that plans to allocate 25% of funding for climate change mitigation. The effectiveness of such plans depends on the extent to which inputs displaced by the transformations induced,

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

both directly and indirectly, by the Covid-19 crisis can be reallocated into green activities, such as renewable energy technologies, building retrofitting, recycling and new infrastructures for the energy and transport sectors. Labor reallocation towards greener sectors is particularly important to reabsorb workers whose demand will permanently displaced by amid the Covid-19 crisis. These concerns apply especially for low-skilled manual workers who experienced a previous deterioration of their employment opportunities associated with globalization and technological change (Autor et al., 2003; Autor et al., 2013).

Because of concerns that the burdens of the Covid-19 crisis fall disproportionately on lower-income households, this paper focuses on manual and unskilled workers. In particular, we provide a qualitative assessment of the difficulties to reallocate low-skilled workers from Covid-19 exposed (i.e. those with low possibility to work-from-home and intense face-to-face interactions) to green occupations. Labor research has shown that reallocation costs are proportional to the skill distance between jobs (e.g., Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010; Guvenen et al., 2020). Therefore, in a scenario of generous green spending, mismatches in the skill, training and educational requirement represent the main barrier for a successful reallocation of workers from origin (e.g., Covid-19 exposed or brown) to destination (green) occupations. Using the Occupation Information Network (O*NET) dataset to retrieve skill intensity scores for detailed US occupations, we compute skill distance measures between origin and destination occupations as well as standard statistics of education and training requirement. As spatial mobility and occupational preferences represent two other important barriers for a successful reallocation, we also compute an index of geographical concentration and a proxy for gender prevalence for each occupation group.

Our analysis reveals that the average green manual occupation requires on average 14 months of on-the-job training compared to 7 months for the average occupation affected by the Covid-19. However, the skill gap between green and generic low-skilled occupations is similar. In other words, the transition from a generic low-skilled occupation to a green low-skilled occupation is as difficult as the transition from a Covid-19 exposed low-skilled occupation to a green low-skilled occupation. While both green and Covid-19 exposed occupations exhibit similar levels of spatial concentration, a potential barrier to a green job reallocation relates to occupational preferences: notably that the former occupations are much more male-oriented than the latter. Finally, the last category of origin occupations, i.e. those mostly employed in polluting sectors (brown), exhibit a skill set similar to that of green occupations, but have a modestly lower training requirements and a significantly higher spatial concentration.

Motivated by the large difference in training requirements between green occupations and other origin occupations, especially Covid-19 exposed, in the second part of the paper we examine whether job training programs increased effectiveness of green spending under the American Recovery and Reinvestment Act (ARRA). ARRA investments were implemented to restart the US economy after the 2008 financial crisis, and included several programs targeting green investments. Following Popp et al. (2020), we exploit variation in the spatial distribution of green ARRA spending across Commuting Zones (CZ henceforth) and estimate how the effectiveness of such spending varies depending on the presence of specific training programs. Popp et al. (2020) provide a comprehensive evaluation of the green ARRA effect along several dimensions, but do not explicitly consider the mediating role of training programs. Here, we complement their work using new data on training programs devoted to the green economy, focusing

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

on both the wage and employment effects of the green stimulus for manual occupations. In doing so, we also contribute to the growing literature on the labor market effects of environmental policies across different skill groups (Marin and Vona, 2019; Yip, 2018). We show that training programs complement green spending, helping create new employment opportunities for workers displaced by other structural transformations, including carbon pricing policies (Yip, 2018; Marin and Vona, 2019) and automation (Acemoglu and Autor, 2011; Frey and Osborne, 2017). Remarkably, we find a positive wage effect for green-manual workers only in CZs with a green training program. This result qualifies that of Popp et al. (2020) who did not find a positive wage effect on average.

Our result informs both the policy debate and the design of theoretical models suitable to examine the effect of a green stimulus in post-pandemic economies. For example, general equilibrium model with search frictions find that climate policies have small aggregated effects on the economy, but trigger a substantial reallocation of labor from brown to green sectors (Hafstead and Williams III, 2018). However, such models are silent on the fundamental determinants of search frictions that are an important component of compliance costs (Bartik, 2015). Our analysis represents a first step towards unpacking the black box of search frictions, making them explicitly dependent on differences in the skill requirement across different occupations or sectors.

On the policy side, our results should be taken with caution as training programs for green jobs may be correlated with green ARRA spending and thus be endogenous. We show, however, that conditional on our set of covariates, the distribution of green ARRA is similar in CZs with or without green training programs. In turn, as in Popp et al. (2020), endogeneity in green ARRA is mitigated by allowing green ARRA to have an effect before the first year of the stimulus and subtracting such pre-trend effect to mitigate endogeneity concerns. It is worth noting, however, that we observe no significant pre-trends for green ARRA on green-manual employment, thus reducing endogeneity concerns compared to Popp et al. (2020), who primarily focus on total employment.

The remainder of the paper is organized as follows. Section II presents the descriptive results based on differences among several dimensions between selected groups of occupations. Section III briefly illustrates the empirical strategy and the results of the econometric analysis. Section IV concludes. Further details are in the Appendices and in the related paper of Popp et al. (2020).

3.2 Green skills distance and profiling of jobs at risk

3.2.1 Definitions

As shown in previous research (Vona et al., 2019; Popp et al., 2020), the first and main effect of a green fiscal stimulus is to create green jobs. In the main analysis of this paper, we define an occupation as green if it requires at least one green specific task[6]. We further qualify our "destination" group, namely the group of occupations that are likely

[6] A more accurate definition of green employment, where the greenness of an occupation is defined as the share of green tasks on total tasks required, is provided by Vona et al. (2018, 2019). In some of the following analysis, we will also use this more accurate and continuous definition of green employment. Occupational greenness of green-growing manual occupations is shown in Table A1 in Appendix A.

"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"

to benefit the most from a green stimulus, as the subset of green manual occupations that experienced a positive employment growth between 2008 and 2017. We focus on manual jobs because most of the jobs created by green ARRA investments were in manual occupations (Popp et al., 2020).

We consider four groups of "origin" occupations that are likely to be harmed either by the Covid-19 crisis or by ambitious green policies. Because we expect that workers from high-skilled occupations will have less difficulty being re-employed, we focus on low-skilled occupations to build our three main groups of "origin" occupations.

The most direct losers from Covid-19 are workers in low-skill jobs characterized by high face-to-face interaction and low possibility of working from home. These were the workers whose jobs were suspended during the different lockdowns to limit the diffusion of the virus. To identify these Covid-19 exposed jobs, we use the two complementary indicators. Dingel and Neiman (2020) develop a binary indicator of teleworking feasibility. An occupation is considered as doable from home based on data from O*NET regarding the occupational work context and generalized work activities. The second O*NET based indicator uses a continuous score (range 0-1) to reflect the importance of face-to-face interaction for each occupation (Mongey et al., 2020). Following Mongey et al. (2020), we define an occupation at risk because Covid-19 if work-from-home is not doable and the importance of face-to-face is above average.

Second, the economic crisis started by Covid-19 will also accelerate long run trends in automation of tasks as companies will look for technological solutions to insure against current and future pandemic-related risks (Chernoff and Warman, 2020). To identify low-skilled occupations exposed to automation, we employ two standard indexes previously used in the literature. First, routine-intensive low-skill occupations are those belonging to the top-decile (weighted by employment in 2017) of Routine Task Intensity index (Acemoglu and Autor, 2011). Second, low-skilled occupations at risk of computerisation are those in the top-decile (weighted by employment in 2017) in the distribution of the probability of computerization built by Frey and Osborne (2017).

Finally, the environmental effectiveness of a green stimulus depends on the substitution of pollution- and resource-intensive industries and products with cleaner industries and products. The demand for occupations that are over-represented in pollution-intensive industries is likely to decline as the green stimulus will accelerate such substitution process. We use the definition of brown jobs in Vona et al. (2018) as the occupations mostly employed in pollution-intensive industries by considering 8 different air emissions.

Note that low-skilled green occupations are only manual, while low- and middle-skills occupations exposed to Covid-19 and automation include service and clerical jobs as well. We will keep all other low-skilled occupations in the comparisons of this section using the well-known fact that it would be easier for low- and middle-skilled workers displaced by Covid-19 to be re-employed in manual green occupations than in abstract green occupations (Cortes, 2016).

Detailed definitions of these occupational groups are reported in Table 1, while the full list of 6-digit SOC occupations in each group is reported in Appendix A. Overall, in 2017 these groups of potential losers account for 53.3% of US employment and 80.8% of US employment in low-skilled occupations (Table 2)[7]. Green manual occupations that

[7] There is some degree of overlap across different categories of losers: 7.4 of all losers belong to 2 different groups while 6.4% belong to 3 different groups.

"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"

grew over 2009-2017 period account for as much as 5.2% of total US employment in 2017. However, if we acknowledge that these green workers devote only a fraction of their time to green tasks and thus reweight for the occupational greenness as a proxy of time spent in green task (see footnote 5 and Vona et al., 2019), just 1% of total worktime is devoted to green tasks. These figures and the fact that the short-term effect of a green stimulus are modest (Popp et al., 2020) imply that even a very generous green stimulus is unlikely to be enough to quickly reabsorb massive layoff of workers in Covid-19-exposed occupations.

Table 1 – Definition of relevant occupational groups

Group of occupations	Description
Destination: occupations that will benefit from a green stimulus package	
Growing (2009-2017) green manual occupations	Manual occupations (SOC 47-53) with strictly positive greenness that experience employment growth in 2009-2017
Growing (2009-2017) green manual occupations (weighted with greenness)	Manual occupations (SOC 47-53) with strictly positive greenness that experience employment growth in 2009-2017. Statistics are weighted by occupational employment multiplied by occupational greenness
Origin: occupations that will be harmed by the Covid-19 lockdown and other structural transformations	
Benchmark: all non-green low-skilled occupations	Non-green occupations in low-skilled SOC groups (33-53)
Low-skilled occupations at risk because of Covid-19	Low-skilled occupations (SOC 33-53) for which work-from-home is not feasible (source: Dingel and Neiman, 2020) and with above-average physical proximity at work using data from Mongey et al. (2020)
Low-skilled occupations with highest RTI (top 10%)	Low-skilled occupations (SOC groups 33-53) in the top decile (i.e. 10% of US employment in 2009) of routine task intensity index (as defined by Acemoglu and Autor, 2011, based on O*NET data)
Low-skilled occupations with highest computerization probability (top 10%)	Low-skilled occupations (SOC groups 33-53) in the top decile (i.e. 10% of US employment in 2009) of computerisation probability (as defined by Frey and Osborne, 2017)
Brown manual occupations	Brown occupations as defined by Vona et al. (2018) in low-skilled SOC groups (33-53)

3.2.2 Descriptive Evidence

Table 2 reports a general profiling of occupational groups across several characteristics. Compared to the benchmark group of low-skilled non-green occupations, green-growing manual jobs exhibit a similar degree of geographical dispersion, offer a 20% wage premium and employ much older workers on average. Notably, green manual occupations are disproportionately biased towards male workers (more than 90%).

As Covid-19 exposed occupations represent the lion's share of low-skilled occupations, it is not surprising that they are very similar to the benchmark group. Low-skilled occupations that are RTI-intensive and with a high-computerization probability also have characteristics similar to those of the benchmark group, and thus have similar differences with green occupations. By contrast, brown occupations are much more similar to green occupations in terms of gender composition, age and wages. However, they are significantly more concentrated spatially. This spatial concentration is a well-known concern for high-carbon communities (Fragkos and Paroussos, 2018), which is largely beyond the scope of this paper.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Table 2 – Profiling of occupational groups

	% of total empl in 2017	Number of 6-digit SOC occupations	% of male employees	Age of employees (average)	Average hourly wage in 2017 (US$)	Locational GINI coefficient
Growing (2009-2017) green manual occupations	5.2%	18	92.6%	43	21.00	0.26
Growing (2009-2017) green manual occupations (weighted with greenness)	1.0%	18	90.3%	42	20.46	0.31
Benchmark: all non-green low-skilled occupations	59.2%	386	50.5%	39	16.97	0.33
Low-skilled occupations at risk because of Covid-19	34.2%	157	56.4%	37	15.57	0.31
Low-skilled occupations with highest RTI (top 10%)	9.8%	53	32.6%	38	14.14	0.32
Low-skilled occupations with highest computerization probability (top 10%)	7.9%	46	35.3%	38	14.99	0.32
Brown manual occupations	2.8%	79	79.3%	43	21.55	0.60

Description of variables: Locational GINI coefficient: average Locational Gini Coefficient (Gabe and Abel, 2012) across CZs based on ACS data for 2017, high values indicate high geographical concentration, low values indicate low geographical concentration (weights: occupational employment in 2017); Average hourly wage in 2017 (US$): average hourly wage from BLS-OES (weights: occupational employment in 2017); Age of employees (average): average age of employees from ACS 2017 (weights: occupational employment in 2017); % of male employees: average share of male employees from ACS 2017 (weights: occupational employment in 2017); % of total employment in 2017: share of total employment in group in 2017.

Table 3 – Skills, Training and Educational requirements

Origin occupational group:	Training requirements (average months)	Education requirements (average)	Green General Skills (average score)	GGS distance wrt growing green manual occupations weighted by employment (2017) in origin occupation (median; Q1 and Q3 in parenthesis)	GGS 'Eng & Tech' distance wrt growing (2009-2017) green manual occupations (median; Q1 and Q3 in parenthesis)
Growing (2009-2017) green manual occupations	14.3	12.3	0.396	0.064 (0.044, 0.101)	0.055 (0.028, 0.085)
Growing (2009-2017) green manual occupations (weighted with greenness)	14.4	12.5	0.397	0.062 (0.043, 0.096)	0.051 (0.028, 0.088)
Benchmark: all non-green low-skilled occupations	6.8	12.1	0.271	0.130 (0.082, 0.185)	0.156 (0.083, 0.248)
Low-skilled occupations at risk because of Covid-19	7.3	11.7	0.284	0.114 (0.074, 0.154)	0.123 (0.074, 0.193)
Low-skilled occupations with highest RTI (top 10%)	5.3	11.9	0.209	0.158 (0.113, 0.234)	0.189 (0.112, 0.348)
Low-skilled occupations with highest computerization probability (top 10%)	4.4	11.9	0.221	0.152 (0.117, 0.208)	0.186 (0.116, 0.273)
Brown manual occupations	11.9	12.1	0.337	0.063 (0.042, 0.097)	0.062 (0.036, 0.114)

Description of variables: Training requirements (average months): average training requirement (in months) based on O*NET (weights: occupational employment in 2017); Education requirements (average years): average education requirement (in years) based on O*NET (weights: occupational employment in 2017); Green General Skills (average score): average score of the four Green General Skills as defined in Vona et al. (2018) based on O*NET data (weights: occupational employment in 2017); GGS (Green General Skills) distance is based on Gathmann and Schönberg (2010) and is defined in equation 1 (median and quartiles are weighted using occupational employment in 2017).

Overall, the age and gender gaps may represent two important barriers for a successful reallocation of unskilled workers towards green jobs, while the wage premium for green occupations likely reflect compositional effects associated with such gaps (e.g., men and older workers earn more). At least some of the differences in gender-orientation of an occupation are due to occupational preferences (Bertrand, 2010). That makes it very unlikely that construction jobs will ever employ a large share of women that lost their jobs in sectors such as tourism and food services. The age gap, in turn, suggests a possible skill gap that will be analysed extensively in Table 3. Indeed, as older workers in green

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

manual workers retire, their know-how is also lost.

Next, we compare the different occupational groups using a measure of skill distance, as well as standard measures of occupational requirements of formal education and training (based on O*NET data). According to a voluminous literature in labor economics (e.g., Gathmann and Schönberg, 2010; Guvenen et al., 2020), skill distance is the crucial element to understand the likelihood of successful job creation in terms of wage earned in the new occupation and re-employability (Gathmann and Schönberg, 2010; Guvenen et al., 2020). To limit the space of possible skills used to build our skill distance measure, we consider only the fourteen green general skills identified by Vona et al. (2018)[8]. We compute a synthetic measure of distance across the 14 items of Green General Skills (GGS henceforth) as the angular separator distance in task importance between pairs of occupations following Gathmann and Schönberg (2010):

$$GGS\_distance_{mn} = 1 - \frac{\sum_{r=1}^{14}(q_{rm} \times q_{rn})}{\left[\left(\sum_{r=1}^{14} q_{rm}^2\right) \times \left(\sum_{r=1}^{14} q_{rn}^2\right)\right]^{1/2}} \quad (1)$$

where q_rm^ and q_rn^ are importance scores (with support 0-1) for GGS item r in, respectively, occupation m and n. To illustrate, consider "Solar Photovoltaic Installers" (SOC 47-2231) as the potential green manual occupation 'of destination'. The distance of all other low-skilled occupations with respect to construction workers ranges from 0.006 for "Plumbers, Pipefitters, and Steamfitters" (SOC 47-2152) to 0.36 for "Door-To-Door Sales Workers, News and Street Vendors, and Related Workers" (SOC 41-9091[9]). This implies that the green general skills that are likely to be in high demand for Construction Laborers could be better performed by a former "Pile-Driver Operator" than by a "Door-To-Door Sales Worker" and, consequently, a successful job-to-job transition is more likely in the former than in the latter case.

Table 3 reports the skill distance measures as well as standard measures of occupational requirements of formal education and training (also based on O*NET data[10]). These standard measures confirm and reinforce the finding by Consoli et al. (2016) about the higher importance of training requirements for green occupations compared to other jobs. Green manual jobs require, on average, twice as much training than non-green low-skill jobs and Covid-19 exposed jobs: 14 months vs. just 7 months of training. The difference with occupations whose tasks are easily replaceable by robots and computers is even larger, while the training gap is somewhat smaller for brown

[8] There are more than 400 items in the O*NET database to be used in computing skill set distances (including work activities, abilities, skills, work context, values, etc.). As we focus on green jobs as a potential destination of job-to-job transition, the set of general skills that are systematically more represented in green jobs is what matters for limiting skill mismatches. We thus consider the set of 'general skills' that were identified to be relevant for green occupations by Vona et al. (2018). These include the following 14 items in O*NET: Engineering and Technology; Design; Building and Construction; Mechanical; Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment; Physics; Biology; Systems Analysis; Systems Evaluation; Updating and Using Relevant Knowledge; Provide Consultation and Advice to Others; Law and Government; Evaluating Information to Determine Compliance with Standards.

[9] The gap in GGS between the “Solar Photovoltaic Installers” and “Door-To-Door Sales Workers” is particularly large for the GGS “Mechanical” (0.73) and “Building and Construction” (0.72) while it is very small for “Biology” (0.03).

[10] In the O*NET database, training is on-the-job training.

*“This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Grant Agreement No **730403**“*

occupations. Conversely, for all the groups of occupations considered, the formal education requirement is very similar ranging from 11.7 years (occupations at risk because of Covid-19) to 12.5 years (green manual weighted by greenness), which corresponds to a high-school degree.

Note that the age gap discussed above is not sufficient to explain such differences in training requirements. If one computes the average month of training per year worked, the differences are still remarkable: 0.61 for green manual jobs versus 0.38 for Covid-19 exposed and 0.32 for the benchmark. Therefore, unless training investments declined dramatically in recent years, the training gap is not simply explained by the age gap.

The gap in training, however, goes beyond the simple difference in average duration of the required preparation. The 7 months of training already acquired by workers in non-green jobs are of little value for green jobs if the content of such training was not related with the set of skills required by green jobs. In contrast, if the training in non-green jobs supplied a set of skills similar to the ones required by green jobs (i.e. GGS), then we should expect an easier job-to-job transition and less need for training investment to increase the productivity of newly hired 'green' workers.

In column 3 of Table 3, we report the average GGS score, i.e. the mean of the fourteen green skills, for each group of occupations. As would be expected from the data-driven methodology used to elicit these green skills (Vona et al., 2018), the score is the highest for green manual occupations. Brown jobs have a very similar score, showing that those jobs require skills comparable to green occupations. However, other vulnerable occupational groups have a significantly lower GGS requirements. To illustrate, a manual green occupation has a GGS score that is 40% higher than the score of a Covid-19 exposed occupation and almost double than the average score of a low-skilled RTI-intensive occupation. Importantly, Covid-19 exposed and automation-exposed occupations are pretty similar to the benchmark in terms of average GGS.

In columns 4 and 5, we present the computations of the distance measures for, respectively, all GGS skills and only engineering and technical skills, which are the most important skills for green manual occupations. We first report the distances within the groups of green manual occupations. Despite the obvious similarities in the green skills sets among green-manual jobs, some differences exist and these differences are of a similar order of magnitude than those between green and brown occupations. These conclusions do not change if we consider engineering and technical skills only (column 5). In line with the findings of Vona et al. (2018), the takeaway is that worker skills need not hinder the transition from brown to green jobs. However, the need of geographical reallocation of brown workers could be an issue, given the large locational Gini coefficient for brown workers.

For occupations at risk because of Covid-19, we find a median GGS distance of 0.11, which stands slightly below the median for all non-green low-skilled occupation but is well above the distance with brown occupations or within green manual occupations. Importantly, the distance for the lower quartile is above the median for green-manual jobs: even the best Covid-19 exposed occupations are harder to re-employ in growing green-manual jobs than within green manual occupations. The skill distance becomes higher if we consider engineering and technical skills. Technical Green General Skills such as “Building and Construction” or “Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment” could be acquired through both formal education and on-the-job training, thus corroborating the idea of investing in specific education and training programs to increase to ease the relocation of displaced workers to green-manual jobs. It

*“This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Grant Agreement No **730403**“*

should be noticed, however, that while training could be effective already in the short term, investments aimed at changing the content of educational programs requires a longer time horizon for the realization of their effects.

Finally, the high median GGS distance for low-skilled routine-intensive jobs and jobs with high probability of computerisation suggests these workers are most likely to struggle finding a new job in growing green-manual occupations. Even the 'best' quartile has a much higher GGS distance than the 'worst' quartile of growing green-manual jobs. In addition, skill distances widen for engineering and technical skills compared to the benchmark of a job-to-job transition within the group of green manual occupations (column 5). This evidence implies that training programs may not suffice for these workers due to skill mismatches that are too large to fill with just on-the-job training. The re-employability of these workers in growing green-manual jobs thus requires time (i.e. more than one year of training) and resources to be invested in training, which represent a substantial burden for the worker, the hiring company or the government, depending on who is paying for the training.

3.3 Methodology

Our analysis in section 2 highlights that growing green-manual jobs require very large amounts of on-the-job training: more than twice the average of low-skilled non-green jobs. While changes in educational programs only influence long run changes in the supply of skills, the provision of training could have an immediate short-term impact and can be especially effective for job-to-job transitions among occupations that require similar levels of formal education. In this section, we focus on the role of local 'specific' training supply as a possible mediating factor to enhance the job-creation of green spending. In subsection A we describe our proxy of local 'specific' training supply and the data on green ARRA, in subsection B we discuss our empirical strategy and in subsection C we comment on the main results.

3.3.1 Data sources and descriptive evidence

The American Recovery and Reinvestment Act (ARRA) was approved by the US administration in 2009 in the aftermath of the economic collapse later labelled as the ‘great recession’. Overall, the stimulus included 350 billion US$ direct spending (our focus here) and 250 billion US$ in tax reductions. Funding was awarded between 2009 and 2012 and was intended to limit the negative consequence of the great recession on jobs. As much as 17% of the stimulus was directed towards projects with environmental benefits awarded by the Department of Energy (14% of total ARRA) and the Environment Protection Agency (3%). This green component of the ARRA stimulus represents a relevant benchmark for any future green fiscal stimulus for its absolute magnitude (about 60 billion US$, or almost 200 US$ per capita) and for its explicit aim of creating jobs (see Popp et al., 2020 for further details).

As a proxy of local capacity to provide green training we collect data from the CareerOneStop tool (Department of Labor) on the presence of locally provided training certifications for green jobs[11]. Data on training by year, ZIP code of the granting

[11] A certification is defined as "*an award you earn to show that you have specific skills or knowledge in an occupation, industry, or technology*" (source: https://www.careeronestop.org/Toolkit/Training/find-certifications.aspx, last accessed: 21 July 2020).

*“This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Grant Agreement No **730403**“*

organisation, and relevant occupations (8-digit SOC) were retrieved from the CareerOneStop website. We define a time-invariant dummy for each CZ which is equal to one if the CZ hosts at least one organisation granting a training certification which is relevant for a green-manual occupation in year 2008.

We focus on the extensive margin of local supply of green training rather than on the intensive margin. The choice was driven by the relatively small number of CZs with training for green-manual jobs (31). Overall, these CZs host 36.4% of the US population, while areas with training that is relevant for non-green manual jobs (43) account for 43.5% of the US population. As in Popp et al. (2020) and Dupor and Mehkari (2016), we consider 587 (out 709) CZs with at least 25,000 residents in 2008: these account for as much as 99.5% of the US population and employment.

3.3.2 Local supply of green training and labor market outcomes: empirical strategy

To evaluate the impact of the green ARRA stimulus on labor market outcomes we use the same framework developed in Popp et al. (2020). We consider both job creation effects and wages for green-manual jobs. In line with the growing literature on the empirical assessment of the ARRA stimulus (see e.g. Dupor and Mehkari, 2016), we estimate the following stacked difference equation for our set of 587 US CZs for the period 2005-2017:

$$\Delta ln(Y_{it}) = \alpha + \sum_{s=pre,short,long} \theta_s \mathrm{GreenTrain}_{\mathrm{i,2008}} + \sum_{s=pre,short,long} \beta_s ln\left(\frac{GreenARRA_i}{pop_{i,2008}}\right) + \sum_{s=pre,short,long} \gamma_s ln\left(\frac{GreenARRA_i}{pop_{i,2008}}\right) \times \mathrm{GreenTrain}_{\mathrm{i,2008}} + \sum_{s=pre,short,long} \mathbf{X}'_{it_0}\boldsymbol{\varphi}_s + \epsilon_{it}. \quad (2)$$

where $\Delta \ln(y_{it})$ is the change in labor market outcome y_{it} between year t and the base year 2008 in CZ i, $\mathrm{GreenTrain}_{\mathrm{i,2008}}$ is a dummy variable for CZs hosting organizations that provide training for green-manual occupations, $\frac{GreenARRA_i}{pop_{i,2008}}$ is the total ARRA spending per capita by the Department of Energy and the Environment Protection Agency in 2009-2012 and X'_{it_0} is a set of time-invariant control variables.[12] We take a log transformation for both our dependent and main explanatory variable to account for the skewness in their respective distributions. To allow for within-region correlation in error terms we cluster standard errors by state. All independent variables are time invariant, measured before the great recession, and are interacted with three time-window dummies: one for the pre-crisis period (*pre*, 2005-2007), one for short term right after the great recession and the ARRA (*short*, 2009-2012), one for the longer term (*long*, 2013-2017). We employ the same set of control variables as in Popp et al. (2020).[13] We account for region-specific trends (US division dummies), for the industry structure of the CZs, for trends in employment prior to the great recession (total and by industry), for exposure to

[12] To ease interpretation, we define the dependent variable $\Delta \ln(y_{i,t}) = ln(y_{i,2008}) - ln(y_{i,t}) = ln\left(\frac{y_{i,2008}}{y_{i,t}}\right)$ for years prior to 2008 and $\Delta \ln(y_{i,t}) = ln(y_{i,t}) - ln(y_{i,2008}) = ln\left(\frac{y_{i,t}}{y_{i,2008}}\right)$ from 2009 onwards, where *y* equals per-capita employment (using population in 2008) or wages.

[13] Details on the definition of variables and data sources are reported in Tables B1 and B2 in Appendix B.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

international trade, for income per capita, for the presence of federal R&D lab and state capitals, for environmental policy stringency and for the potential for renewable energy generation and shale gas extraction. Moreover, we account in a flexible way for the possible impact of ARRA spending from Departments and Agencies other than DoE and EPA by including dummy variables for vigintiles of non-green ARRA spending per capita.

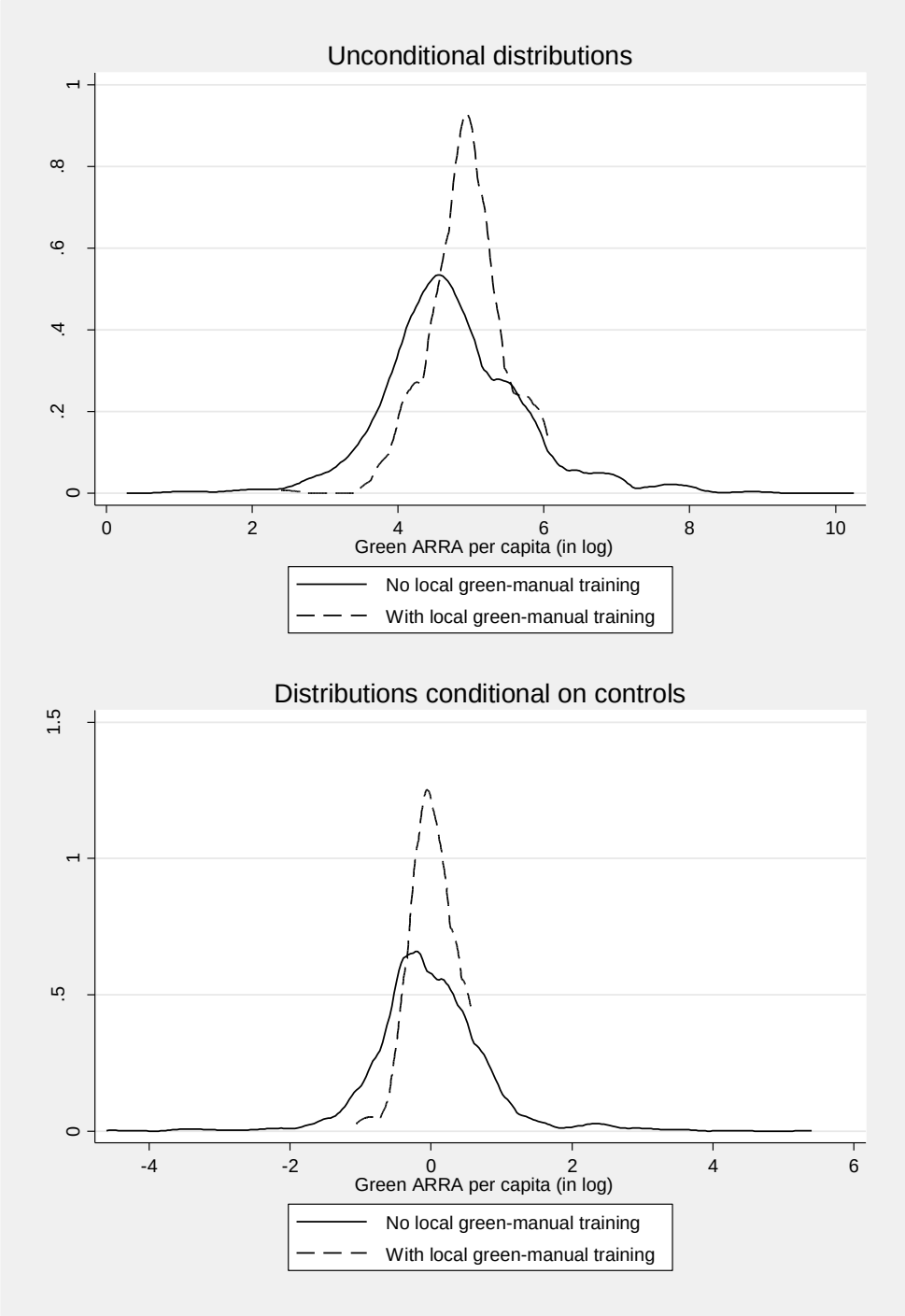
Even though we control for a large number of observables to limit concerns related to the non-random assignment of green ARRA across areas, one possible source of endogeneity remains: the potential for heterogeneous trends in labor market outcomes across areas that later received different amounts of green ARRA spending. We circumvent this issue by explicitly computing the effect of green ARRA (either short $\hat{\beta}_{short}$ or long $\hat{\beta}_{long}$) net of pretrends $\hat{\beta}_{pre}$. Deviations from pre-trends represent the actual additional job creation (or wage increase) effects induced by green ARRA, above and beyond pre-existing trends (see Popp et al., 2020 for a comprehensive discussion of endogeneity issues in this setup).

An additional endogeneity issue in our setting concerns the non-random assignment of green ARRA between areas with or without manual training. As green-manual training supply is not randomly assigned to CZs, it is important to understand to what extent it is correlated with green ARRA. In columns 1-3 of Table B2 in Appendix B we show some simple cross-sectional OLS relationship between our proxy for green-manual training and green ARRA. While the unconditional relationship (column 1) suggests that green ARRA per capita was significantly larger in area with local green-manual training, this difference fades out once we control for other observable characteristics of the CZ.[14] From a graphical viewpoint, we can see from Figure 1 that the unconditional distribution of green ARRA per capita for areas with local green-manual training is shifted to the right compared to other areas (top panel) while, once we partial-out for confounding factors, the two distribution turn out to be much more similar (bottom panel). In column 4 of Table B2 in Appendix B we show that the presence of local 'green-manual' training is positively correlated with the size of the CZ, with its initial endowment of GGS, and with the presence of federal R&D labs, while it is negatively correlated with growing unemployment rates. Accounting for these observable characteristics is thus crucial to limit omitted variable bias.

[14] We include the same set of control variables used in the main specification of Popp et al. (2020). A detailed description of variables and data sources is reported in Table B1 in Appendix B.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Figure 1 – Unconditional and conditional distributions of green ARRA per capita (in log) for areas with or without local green-manual training



3.3.3 Results

Table 4 presents our estimates of the effects of green ARRA on labor market outcomes as mediated by the availability of green training programs in the local labor market. We report results on employment (column 1) and wages (column 2) for green

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

manual employment[15]. As an extension, in Table 5 we replicate the same analysis replacing green training programs with non-green ones as a mediating factor. In commenting, we focus on the difference between the long- (or short-) term coefficient and the pre-trend coefficient of green ARRA. This provides a conservative interpretation of the effect of green ARRA on employment, as we find no significant evidence of pre-trends in communities receiving more green ARRA investments. Finally, as a robustness check (Table B3 in Appendix B), we also consider explicitly CZ size as a possible confounding factor.

Green stimulus spending is significantly more effective at improving the working conditions (both average hourly wage and employability) of green-manual jobs in areas with training facilities for green manual jobs. Indeed, in column 1 the interaction terms between green ARRA per capita and local training for green-manual jobs is positive and significantly different from zero both in the short and in the long run. The effect on wages is also particularly strong for these green manual workers. For employment, the estimates of the overall job creation effect (i.e. accounting for pre-trends) for green manual workers are imprecisely estimated (p-value = 0.103), probably due to the small number of workers in this group. On average, 1 million US$ of green ARRA in CZs with local training supply for green-manual jobs creates 5.5 green-manual jobs in the long run (2013-2017), while it just creates 1.96 green-manual jobs in CZs without any local supply of green-manual training over the same timespan (see Table 6). To put these results into context, Popp et al. (2020) find that 1 million US$ of green ARRA creates, on average, about 14.76 jobs, 13.74 of which in manual jobs.

Our results in Table 5 show that non-green training programs have positive but smaller effects. However, we still observe an increase in wages for manual green workers, suggesting that non-green training programs for manual workers help increase the productivity of green-manual workers for performing their non-green tasks, thus contributing to increasing average occupational wages.

Comparing these results to those in Popp et al. (2020) reveals both important similarities and some noteworthy differences. Recall that Popp et al. (2020) use the same empirical strategy except for the addition of the green training program dummy interacted with the pre-, short- and post- dummies.

In terms of similarities, the bulk of the green ARRA effect occurs in the long-run. The one exception is a significant short-term effect for areas with local training on wages for green-manual jobs. Moreover, Popp et al. (2020) also find that the issue of pre-trends in green ARRA effects is far less problematic for manual and green labor than for total employment, which further mitigates the main endogeneity concern in our empirical setup[16].

The most important difference when considering job training is the emergence of a positive wage effect for green manual workers in areas offering the appropriate training for green jobs. This result provides more nuance the conclusion of Popp et al. (2020), who find that green spending can improve the employability of low-skilled manual workers, but not their wages. Instead, our results suggest that, if green spending is

[15] Both measures are weighted by occupation greenness as a proxy of share of worktime spent in performing green tasks (Vona et al., 2018). The motivation is that a green fiscal stimulus as the green component of ARRA increases the demand for green tasks rather than green jobs in general.

[16] The main result of Popp et al. (2020) on total employment and sector-level employment are not altered by the inclusion of the training dummy. Results are available upon request by the authors.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

combined with the appropriate training, the productivity of unskilled workers will increase together with their wages and thus the overall job quality.

One potential concern is the systematic concentration of green training supply in densely populated areas. Might our results simply be picking up the benefits of agglomeration in urban economies? To verify this is not the case, we consider a specification where we account for CZ size as an additional mediating factor. More specifically, we interact green ARRA per capita not only with the dummy for the presence of local training for green manual jobs, but also with a dummy for CZs in the top quartile in terms of population in 2008. Results, shown in Table B3 in Appendix B, show that sign and magnitude of the effects remain unaffected compared to our baseline results in Table 4, thus confirming our findings, while standard errors tend to increase compared to Table 4 when considering green-manual employment as dependent variable. What is important here, however, is that larger CZs did not gain more per se from green ARRA in terms of green-manual job creation and wages for green-manual workers.

While we cannot definitively rule out all possible endogeneity, our results suggest that combining green spending and targeted training investments to improve the working conditions of the left-behind seems a promising avenue to improve the design of green fiscal stimulus. Further research, particularly using micro-economic data on training participants, would help corroborate this suggestive finding.

Table 4 – Differential effect of green ARRA for areas with local green-manual training

Dep var: Change in log outcome variable compared to 2008	(1) Green employment (O*NET-based) in manual occupations per capita	(2) Average hourly wage in manual green occupations
Dummy for local green-manual training in 2008 x D2005_2007	0.0712	-0.222
	(0.190)	(0.170)
Dummy for local green-manual training in 2008 x D2009_2012	0.356*	0.313*
	(0.202)	(0.170)
Dummy for local green-manual training in 2008 x D2013_2017	0.415**	0.802***
	(0.181)	(0.166)
Green ARRA per capita (log) x D2005_2007	-0.00304	-0.00982
	(0.00671)	(0.00817)
Green ARRA per capita (log) x D2009_2012	0.000442	0.00837
	(0.00651)	(0.00782)
Green ARRA per capita (log) x D2013_2017	0.0175**	0.00921
	(0.00856)	(0.00860)
Green ARRA per capita (log) x	0.0109	-0.0272
Dummy for local green-manual training in 2008 x D2005_2007	(0.0202)	(0.0180)
Green ARRA per capita (log) x	0.0381*	0.0347*
Dummy for local green-manual training in 2008 x D2009_2012	(0.0213)	(0.0183)
Green ARRA per capita (log) x	0.0478**	0.0904***
Dummy for local green-manual training in 2008 x D2013_2017	(0.0199)	(0.0183)
Comparison across periods and training:		
- Dummy for local green-manual training = 0		
Green ARRA per capita (log): 2009-2012 vs 2005-2007	0.00348	0.0182
s.e.	(0.0119)	(0.0154)
Green ARRA per capita (log): 2013-2017 vs 2005-2007	0.0206	0.0190
s.e.	(0.0134)	(0.0162)
- Dummy for local green-manual training = 1		
Green ARRA per capita (log): 2009-2012 vs 2005-2007	0.0307	0.0801***
s.e.	(0.0376)	(0.0272)
Green ARRA per capita (log): 2013-2017 vs 2005-2007	0.0576	0.137***
s.e.	(0.0347)	(0.0306)
R squared	0.220	0.238

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008. N of CZ: 587. N of observations: 7631. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Year dummies included. Additional control variables (interacted with D2002_2007, D2009_2012 and D2013_2017 dummies): US-Division dummies, Vigintiles of non-green ARRA per capita, Population 2008 (log), Income per capita (2005), Import penetration (year 2005), Pre trend (2000-2007) empl manufacturing / pop, Pre trend (2000-2007) employment tot / pop, Pre trend (2000-2007) empl constr / pop, Pre trend (2000-2007) empl extractive / pop, Pre trend (2000-2007) empl public sect / pop, Pre trend (2000-2007) unempl / pop, Pre trend (2000-2007) empl edu health / pop, Empl manuf 2008 / pop, Empl constr 2008 / pop, Empl extractive 2008 / pop, Empl public sect 2008 / pop, Unempl 2008 / pop, Empl edu health 2008 / pop, Shale gas extraction in CZ interacted with year dummies, Potential for wind energy interacted with year dummies, Potential for photovoltaic energy interacted with year dummies, Federal R&D lab, CZ hosts the state capital, Nonattainment CAA old standards, Nonattainment CAA new standards.

Table 5 – Differential effect of green ARRA for areas with local nongreen-manual training

Dep var: Change in log outcome variable compared to 2008	(1) Green employment (O*NET-based) in manual occupations per capita	(2) Average hourly wage in manual green occupations
Dummy for local nongreen-manual training in 2008 x D2005_2007	0.0385	-0.230
	(0.200)	(0.158)
Dummy for local nongreen-manual training in 2008 x D2009_2012	-0.0161	0.168
	(0.165)	(0.133)
Dummy for local nongreen-manual training in 2008 x D2013_2017	0.115	0.209
	(0.190)	(0.185)
Green ARRA per capita (log) x D2005_2007	-0.00316	-0.00861
	(0.00687)	(0.00834)
Green ARRA per capita (log) x D2009_2012	0.00217	0.00821
	(0.00675)	(0.00791)
Green ARRA per capita (log) x D2013_2017	0.0182**	0.0107
	(0.00880)	(0.00896)
Green ARRA per capita (log) x	0.00544	-0.0281
Dummy for local nongreen-manual training in 2008 x D2005_2007	(0.0214)	(0.0175)
Green ARRA per capita (log) x	-0.000469	0.0146
Dummy for local nongreen-manual training in 2008 x D2009_2012	(0.0176)	(0.0144)
Green ARRA per capita (log) x	0.0182	0.0244
Dummy for local nongreen-manual training in 2008 x D2013_2017	(0.0212)	(0.0216)
Comparison across periods and training:		
- Dummy for local nongreen-manual training = 0		
Green ARRA per capita (log): 2009-2012 vs 2005-2007	0.00533	0.0168
s.e.	(0.0124)	(0.0157)
Green ARRA per capita (log): 2013-2017 vs 2005-2007	0.0214	0.0193
s.e.	(0.0139)	(0.0167)
- Dummy for local nongreen-manual training = 1		
Green ARRA per capita (log): 2009-2012 vs 2005-2007	-0.000581	0.0596**
s.e.	(0.0312)	(0.0248)
Green ARRA per capita (log): 2013-2017 vs 2005-2007	0.0341	0.0719**
s.e.	(0.0354)	(0.0322)
R squared	0.219	0.234

OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008. N of CZ: 587. N of observations: 7631. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Year dummies included. Additional control variables (interacted with D2002_2007, D2009_2012 and D2013_2017 dummies): US-Division dummies, Vigintiles of non-green ARRA per capita, Population 2008 (log), Income per capita (2005), Import penetration (year 2005), Pre trend (2000-2007) empl manufacturing / pop, Pre trend (2000-2007) employment tot / pop, Pre trend (2000-2007) empl constr / pop, Pre trend (2000-2007) empl extractive / pop, Pre trend (2000-2007) empl public sect / pop, Pre trend (2000-2007) unempl / pop, Pre trend (2000-2007) empl edu health / pop, Empl manuf 2008 / pop, Empl constr 2008 / pop, Empl extractive 2008 / pop, Empl public sect 2008 / pop, Unempl 2008 / pop, Empl edu health 2008 / pop, Shale gas extraction in CZ interacted with year dummies, Potential for wind energy interacted with year dummies, Potential for photovoltaic energy interacted with year dummies, Federal R&D lab, CZ hosts the state capital, Nonattainment CAA old standards, Nonattainment CAA new standards.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Table 6 – Quantification of effects: green manual job creation per 1 million US$ green ARRA

N of green-manual jobs created for 1 million US$ of green ARRA	Green-manual training	Non green-manual training
- Dummy for local training = 0		
Green ARRA per capita (log): 2009-2012 vs 2005-2007	0.29	0.44
s.e.	(0.99)	(1.03)
Green ARRA per capita (log): 2013-2017 vs 2005-2007	1.96	2.03
s.e.	(1.28)	(1.32)
- Dummy for local training =		
Green ARRA per capita (log): 2009-2012 vs 2005-2007	2.57	-0.05
s.e.	(3.15)	(2.60)
Green ARRA per capita (log): 2013-2017 vs 2005-2007	5.50	3.25
s.e.	(3.32)	(3.37)

3.4 Concluding Remarks

In this paper we consider whether gaps in green skills across occupational groups might affect the impact of green stimulus investments, focusing on the likely losers from the Covid-19 pandemic and likely winners from a green fiscal stimulus (i.e. green-manual jobs). Our results highlight that low-skilled occupations exposed to social distancing measures introduced by governments in response to Covid-19 as well as automatable occupations possess a skill-set that is not in line with the one required by green-manual jobs. On the other hand, low-skilled jobs in emission-intensive industries could be more easily employed in green-manual jobs as they already possess an adequate set of green skills.

If gaps in green skills could be relevant barriers to re-employing displaced jobs, specific training could represent a natural solution as it provides workers with the skills required in performing high-demand green tasks. We provide evidence about the role of green training local supply as a possible enabling factor in the creation of jobs by means of green fiscal stimulus by considering the green component of the American Recovery and Reinvestment Act of 2009. Our results point to the relevance of local green training supply to create jobs from green fiscal stimulus and to the strong positive influence of local green training on wages of green-manual jobs.

Our results point to two complementary policy implications. First, jobs at risk because of Covid-19 differ substantially in their skill set compared to green-manual jobs, which are the expected winners of a green fiscal stimulus. This result implies that a green fiscal stimulus, though contributing to combating climate change, might not be effective in also boosting re-employment opportunities for workers displaced by social distancing measures. Second, the potential for creating green jobs crucially depends on the availability of green training to close the green skills gap between displaced workers and jobs in high-demand because of a green fiscal stimulus.

Further research is needed, however, to better understand the effectiveness of green training as a tool to increase the supply of green skills. Access to microeconomic data for specific green training programs combined with worker-level data would make it possible to account for self-selection into training programs, migration, and other possible confounding factors. Our results suggest this is a topic deserving of further study.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

References

Acemoglu D, Autor D (2011) Skills, tasks and technologies: implications for employment and earnings. In Ashenfelter O, Card DE (eds.) Handbook of Labor Economics Volume 4, Elsevier, Amsterdam NL

Agrawala S, Dussaux D, Monti N (2020) What policies for greening the crisis response and economic recovery? Lessons learned from past green stimulus measures and implications for the COVID-19 crisis. OECD Environment Working Papers, No. 164, OECD Publishing, Paris

Autor D, Levy F, Murnane J (2003) The skill content of recent technological change: an empirical exploration. Quarterly Journal of Economics 118(4):1279-1333

Autor D, Dorn D, Hanson G (2013) The Chyna Syndrome: local labor market effects of import competition in the United States. American Economic Review 103(6):2121-2168

Bartik TJ (2015) The social value of job loss and its effect on the costs of U.S. environmental regulations. Review of Environmental Economics and Policy 9(2):179–97

Bertrand M (2010) New perspectives on gender. In Ashenfelter O, Card D (Eds.), Handbook of labor economics (Vol. 4b, pp. 1545–1592). Amsterdam, The Netherlands: Elsevier

Chernoff AW, Warman C (2020) COVID-19 and implications for automation. NBER Working Paper no. 27249

Consoli D, Marin G, Marzucchi A, Vona F (2016) Do green jobs differ from non-green jobs in terms of skills and human capital? Research Policy 45(5):1046-1060

Cortes GM (2016) Where have the middle-wage workers gone? A study of polarization using panel data. Journal of Labor Economics 34(1):63-105

Dingel JI, Neiman B (2020) How many jobs can be done at home? BFI Working Paper, available at https://bfi.uchicago.edu/working-paper/how-many-jobs-can-be-done-at-home/

Dupor B, Mehkari MS (2016) The 2009 Recovery Act: Stimulus at the extensive and intensive labor margins. European Economic Review 85:208-228

Fragkos P, Paroussos L (2018) Employment creation in EU related to renewables expansion. Applied Energy 230:935-945

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Frey CB, Osborne MA (2017) The future of employment: how susceptible are jobs to computerisation? Technological Forecasting and Social Change 114:254-280

Gabe TM, Abel JR (2012) Specialized knowledge and the geographic concentration of occupations. Journal of Economic Geography 12(2):435-453

Gathmann C, Schönberg U (2010) How general is human capital? A task-based approach. Journal of Labor Economics 28(1):1-49

Guvenen F, Kuruscu B, Tanaka S, Wiczer D (2020) Multidimensional Skill Mismatch. American Economic Journal: Macroeconomics 12(1):210-244

Hafstead MAC, Williams III RC (2018) Unemployment and environmental regulation in general equilibrium. Journal of Public Economics 160:50-65

Helm D (2020) The environmental impacts of the coronavirus. Environmental and Resource Economics 76:21–38

Kambourov G, Manovskii I (2009) Occupational specificity of human capital. International Economic Review 50(1):63-115

Marin G, Vona F (2019) Climate policies and skill-biased employment dynamics: evidence from EU countries. Journal of Environmental and Management 98:102253

Mongey S, Pilossoph L, Weinberg A (2020) Which workers bear the burden of social distancing policies? NBER Working Paper no. 27085

Popp D, Vona F, Marin G, Chen Z (2020) The employment impact of green fiscal push: evidence from the American Recovery Act. NBER Working Paper no. 27321

Vona F, Marin G, Consoli D, Popp D (2018) Environmental regulation and green skills: an empirical exploration. Journal of the Association of Environmental and Resource Economists 5(4):713-753

Vona F, Marin G, Consoli D (2019) Measures, drivers and effects of green employment: evidence from US local labor markets, 2006-2014. Journal of Economic Geography 19(5):1021-1048

Yip CM (2018) On the labor market consequences of environmental taxes. Journal of Environmental Economics and Management 89:136-152

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Appendix A – Lists of occupations by occupational group

Table A1 – Growing (2009-2017) green-manual occupations

SOC	Description	Greenness
47-2061	Construction Laborers	0.16
47-2152	Plumbers, Pipefitters, and Steamfitters	0.24
47-2181	Roofers	0.30
47-4011	Construction and Building Inspectors	0.26
47-4041	Hazardous Materials Removal Workers	1.00
49-3023	Automotive Service Technicians and Mechanics	0.22
49-3031	Bus and Truck Mechanics and Diesel Engine Specialists	0.15
49-9021	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	0.13
49-9071	Maintenance and Repair Workers, General	0.13
49-9099	Installation, Maintenance, and Repair Workers, All Other	1.00
51-2011	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	0.13
51-8011	Nuclear Power Reactor Operators	0.28
51-8099	Plant and System Operators, All Other	1.00
51-9012	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders	0.05
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers	0.06
51-9199	Production Workers, All Other	1.00
53-3032	Heavy and Tractor-Trailer Truck Drivers	0.09
53-6051	Transportation Inspectors	0.15

Table A2 – Low-skilled occupations at risk because of Covid-19

SOC	Description
	Other low- and middle-skills occupations (service, clerical, sales)
33-1011	First-Line Supervisors of Correctional Officers
33-1012	First-Line Supervisors of Police and Detectives
33-1021	First-Line Supervisors of Fire Fighting and Prevention Workers
33-2011	Firefighters
33-3011	Bailiffs
33-3012	Correctional Officers and Jailers
33-3021	Detectives and Criminal Investigators
33-3031	Fish and Game Wardens
33-3051	Police and Sheriff's Patrol Officers
33-3052	Transit and Railroad Police
33-9032	Security Guards
33-9091	Crossing Guards
33-9093	Transportation Security Screeners
35-1011	Chefs and Head Cooks
35-1012	First-Line Supervisors of Food Preparation and Serving Workers
35-2011	Cooks, Fast Food
35-2012	Cooks, Institution and Cafeteria
35-2014	Cooks, Restaurant
35-2015	Cooks, Short Order
35-2021	Food Preparation Workers
35-3011	Bartenders
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food
35-3022	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop
35-3031	Waiters and Waitresses
35-3041	Food Servers, Nonrestaurant
35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers
35-9031	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop
37-1012	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers
37-3011	Landscaping and Groundskeeping Workers
37-3012	Pesticide Handlers, Sprayers, and Applicators, Vegetation
37-3013	Tree Trimmers and Pruners
39-1011	Gaming Supervisors
39-1012	Slot Supervisors
39-2021	Nonfarm Animal Caretakers
39-3012	Gaming and Sports Book Writers and Runners
39-3091	Amusement and Recreation Attendants
39-3092	Costume Attendants

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

SOC	Description
39-3093	Locker Room, Coatroom, and Dressing Room Attendants
39-4011	Embalmers
39-4021	Funeral Attendants
39-4031	Morticians, Undertakers, and Funeral Directors
39-5011	Barbers
39-5012	Hairdressers, Hairstylists, and Cosmetologists
39-5092	Manicurists and Pedicurists
39-5093	Shampooers
39-5094	Skincare Specialists
39-6011	Baggage Porters and Bellhops
39-6012	Concierges
39-7011	Tour Guides and Escorts
39-7012	Travel Guides
39-9021	Personal Care Aides
39-9031	Fitness Trainers and Aerobics Instructors
41-1011	First-Line Supervisors of Retail Sales Workers
41-2011	Cashiers
41-2012	Gaming Change Persons and Booth Cashiers
41-2021	Counter and Rental Clerks
41-2022	Parts Salespersons
41-2031	Retail Salespersons
41-9011	Demonstrators and Product Promoters
41-9022	Real Estate Sales Agents
41-9091	Door-to-Door Sales Workers, News and Street Vendors, and Related Workers
43-2021	Telephone Operators
43-3041	Gaming Cage Workers
43-3071	Tellers
43-4121	Library Assistants, Clerical
43-4181	Reservation and Transportation Ticket Agents and Travel Clerks
43-5051	Postal Service Clerks
43-5081	Stock Clerks and Order Fillers
45-2011	Agricultural Inspectors
45-2041	Graders and Sorters, Agricultural Products
45-4011	Forest and Conservation Workers
	Manual occupations
47-1011	First-Line Supervisors of Construction Trades and Extraction Workers
47-2011	Boilermakers
47-2021	Brickmasons and Blockmasons
47-2022	Stonemasons
47-2031	Carpenters
47-2051	Cement Masons and Concrete Finishers
47-2053	Terrazzo Workers and Finishers
47-2061	Construction Laborers
47-2072	Pile-Driver Operators
47-2111	Electricians
47-2121	Glaziers
47-2151	Pipelayers
47-2152	Plumbers, Pipefitters, and Steamfitters
47-2171	Reinforcing Iron and Rebar Workers
47-2181	Roofers
47-2211	Sheet Metal Workers
47-2221	Structural Iron and Steel Workers
47-2231	Solar Photovoltaic Installers
47-3011	Helpers--Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters
47-3012	Helpers--Carpenters
47-3013	Helpers--Electricians
47-3014	Helpers--Painters, Paperhangers, Plasterers, and Stucco Masons
47-3015	Helpers--Pipelayers, Plumbers, Pipefitters, and Steamfitters
47-3016	Helpers--Roofers
47-4031	Fence Erectors
47-4041	Hazardous Materials Removal Workers
47-4051	Highway Maintenance Workers
47-4061	Rail-Track Laying and Maintenance Equipment Operators

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

SOC	Description
47-4071	Septic Tank Servicers and Sewer Pipe Cleaners
47-5011	Derrick Operators, Oil and Gas
47-5012	Rotary Drill Operators, Oil and Gas
47-5013	Service Unit Operators, Oil, Gas, and Mining
47-5031	Explosives Workers, Ordnance Handling Experts, and Blasters
47-5061	Roof Bolters, Mining
47-5071	Roustabouts, Oil and Gas
47-5081	Helpers--Extraction Workers
49-1011	First-Line Supervisors of Mechanics, Installers, and Repairers
49-2091	Avionics Technicians
49-2094	Electrical and Electronics Repairers, Commercial and Industrial Equipment
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay
49-9011	Mechanical Door Repairers
49-9012	Control and Valve Installers and Repairers, Except Mechanical Door
49-9031	Home Appliance Repairers
49-9041	Industrial Machinery Mechanics
49-9043	Maintenance Workers, Machinery
49-9044	Millwrights
49-9045	Refractory Materials Repairers, Except Brickmasons
49-9051	Electrical Power-Line Installers and Repairers
49-9071	Maintenance and Repair Workers, General
49-9081	Wind Turbine Service Technicians
49-9092	Commercial Divers
49-9095	Manufactured Building and Mobile Home Installers
49-9096	Riggers
49-9097	Signal and Track Switch Repairers
49-9098	Helpers--Installation, Maintenance, and Repair Workers
51-2031	Engine and Other Machine Assemblers
51-2091	Fiberglass Laminators and Fabricators
51-2092	Team Assemblers
51-2093	Timing Device Assemblers and Adjusters
51-3021	Butchers and Meat Cutters
51-3022	Meat, Poultry, and Fish Cutters and Trimmers
51-3023	Slaughterers and Meat Packers
51-3093	Food Cooking Machine Operators and Tenders
51-4061	Model Makers, Metal and Plastic
51-4062	Patternmakers, Metal and Plastic
51-4071	Foundry Mold and Coremakers
51-4072	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic
51-9041	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders
51-9191	Adhesive Bonding Machine Operators and Tenders
53-2011	Airline Pilots, Copilots, and Flight Engineers
53-2012	Commercial Pilots
53-2022	Airfield Operations Specialists
53-2031	Flight Attendants
53-3011	Ambulance Drivers and Attendants, Except Emergency Medical Technicians
53-3021	Bus Drivers, Transit and Intercity
53-3022	Bus Drivers, School or Special Client
53-3041	Taxi Drivers and Chauffeurs
53-4041	Subway and Streetcar Operators
53-5011	Sailors and Marine Oilers
53-5021	Captains, Mates, and Pilots of Water Vessels
53-5022	Motorboat Operators
53-5031	Ship Engineers
53-6021	Parking Lot Attendants
53-6061	Transportation Attendants, Except Flight Attendants
53-7062	Laborers and Freight, Stock, and Material Movers, Hand
53-7064	Packers and Packagers, Hand

Table A3 – Low-skilled occupations with highest RTI (top 10%)

SOC	Description
	Other low- and middle-skills occupations (service, clerical, sales)

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

SOC	Description
35-2015	Cooks, Short Order
35-2021	Food Preparation Workers
35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers
39-3012	Gaming and Sports Book Writers and Runners
39-3021	Motion Picture Projectionists
39-3031	Ushers, Lobby Attendants, and Ticket Takers
39-3091	Amusement and Recreation Attendants
41-2011	Cashiers
41-2012	Gaming Change Persons and Booth Cashiers
41-9012	Models
41-9041	Telemarketers
43-2011	Switchboard Operators, Including Answering Service
43-2021	Telephone Operators
43-3021	Billing and Posting Clerks
43-3051	Payroll and Timekeeping Clerks
43-3071	Tellers
43-4021	Correspondence Clerks
43-4151	Order Clerks
43-5051	Postal Service Clerks
43-5053	Postal Service Mail Sorters, Processors, and Processing Machine Operators
43-6013	Medical Secretaries
43-9041	Insurance Claims and Policy Processing Clerks
43-9051	Mail Clerks and Mail Machine Operators, Except Postal Service
43-9061	Office Clerks, General
45-2041	Graders and Sorters, Agricultural Products
	Manual Occupations
47-5041	Continuous Mining Machine Operators
49-9093	Fabric Menders, Except Garment
51-2021	Coil Winders, Tapers, and Finishers
51-3022	Meat, Poultry, and Fish Cutters and Trimmers
51-3023	Slaughterers and Meat Packers
51-4031	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic
51-4035	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic
51-4071	Foundry Mold and Coremakers
51-4072	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic
51-4122	Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders
51-5111	Prepress Technicians and Workers
51-5112	Printing Press Operators
51-5113	Print Binding and Finishing Workers
51-6011	Laundry and Dry-Cleaning Workers
51-6021	Pressers, Textile, Garment, and Related Materials
51-6031	Sewing Machine Operators
51-6041	Shoe and Leather Workers and Repairers
51-6042	Shoe Machine Operators and Tenders
51-6063	Textile Knitting and Weaving Machine Setters, Operators, and Tenders
51-6091	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers
51-7042	Woodworking Machine Setters, Operators, and Tenders, Except Sawing
51-9031	Cutters and Trimmers, Hand
51-9041	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders
51-9083	Ophthalmic Laboratory Technicians
51-9111	Packaging and Filling Machine Operators and Tenders
51-9123	Painting, Coating, and Decorating Workers
51-9197	Tire Builders
53-7021	Crane and Tower Operators

Table A4 – Low-skilled occupations with highest computerization probability (top 10%)

SOC	Description
	Other low- and middle-skills occupations (service, clerical, sales)
35-9031	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop
37-3012	Pesticide Handlers, Sprayers, and Applicators, Vegetation
39-3021	Motion Picture Projectionists
41-2011	Cashiers

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

SOC	Description
41-2021	Counter and Rental Clerks
41-2022	Parts Salespersons
41-9012	Models
41-9021	Real Estate Brokers
41-9041	Telemarketers
43-2021	Telephone Operators
43-3031	Bookkeeping, Accounting, and Auditing Clerks
43-3051	Payroll and Timekeeping Clerks
43-3061	Procurement Clerks
43-3071	Tellers
43-4011	Brokerage Clerks
43-4041	Credit Authorizers, Checkers, and Clerks
43-4071	File Clerks
43-4141	New Accounts Clerks
43-4151	Order Clerks
43-5011	Cargo and Freight Agents
43-5071	Shipping, Receiving, and Traffic Clerks
43-6012	Legal Secretaries
43-9021	Data Entry Keyers
43-9041	Insurance Claims and Policy Processing Clerks
45-4023	Log Graders and Scalers
	Manual Occupations
49-9061	Camera and Photographic Equipment Repairers
49-9064	Watch Repairers
51-2023	Electromechanical Equipment Assemblers
51-2092	Team Assemblers
51-2093	Timing Device Assemblers and Adjusters
51-4035	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic
51-5111	Prepress Technicians and Workers
51-6042	Shoe Machine Operators and Tenders
51-6051	Sewers, Hand
51-6061	Textile Bleaching and Dyeing Machine Operators and Tenders
51-7042	Woodworking Machine Setters, Operators, and Tenders, Except Sawing
51-9021	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders
51-9022	Grinding and Polishing Workers, Hand
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers
51-9081	Dental Laboratory Technicians
51-9083	Ophthalmic Laboratory Technicians
51-9111	Packaging and Filling Machine Operators and Tenders
51-9151	Photographic Process Workers and Processing Machine Operators
51-9194	Etchers and Engravers
53-3031	Driver/Sales Workers
53-6011	Bridge and Lock Tenders

Table A5 –Manual brown occupations (Vona et al., 2018)

SOC	Description
47-4071	Septic Tank Servicers and Sewer Pipe Cleaners
47-5011	Derrick Operators, Oil and Gas
47-5012	Rotary Drill Operators, Oil and Gas
47-5013	Service Unit Operators, Oil, Gas, and Mining
47-5021	Earth Drillers, Except Oil and Gas
47-5031	Explosives Workers, Ordnance Handling Experts, and Blasters
47-5042	Mine Cutting and Channeling Machine Operators
47-5051	Rock Splitters, Quarry
47-5061	Roof Bolters, Mining
47-5071	Roustabouts, Oil and Gas
47-5081	Helpers--Extraction Workers
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay
49-9012	Control and Valve Installers and Repairers, Except Mechanical Door
49-9041	Industrial Machinery Mechanics
49-9043	Maintenance Workers, Machinery
49-9045	Refractory Materials Repairers, Except Brickmasons

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

SOC	Description
49-9051	Electrical Power-Line Installers and Repairers
49-9093	Fabric Menders, Except Garment
51-1011	First-Line Supervisors of Production and Operating Workers
51-2091	Fiberglass Laminators and Fabricators
51-3091	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders
51-3092	Food Batchmakers
51-3093	Food Cooking Machine Operators and Tenders
51-4021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic
51-4022	Forging Machine Setters, Operators, and Tenders, Metal and Plastic
51-4023	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic
51-4033	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4051	Metal-Refining Furnace Operators and Tenders
51-4052	Pourers and Casters, Metal
51-4062	Patternmakers, Metal and Plastic
51-4071	Foundry Mold and Coremakers
51-4191	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic
51-4192	Layout Workers, Metal and Plastic
51-4193	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic
51-4194	Tool Grinders, Filers, and Sharpeners
51-6061	Textile Bleaching and Dyeing Machine Operators and Tenders
51-6063	Textile Knitting and Weaving Machine Setters, Operators, and Tenders
51-6064	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders
51-6091	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers
51-6093	Upholsterers
51-7011	Cabinetmakers and Bench Carpenters
51-7021	Furniture Finishers
51-7031	Model Makers, Wood
51-7032	Patternmakers, Wood
51-7041	Sawing Machine Setters, Operators, and Tenders, Wood
51-7042	Woodworking Machine Setters, Operators, and Tenders, Except Sawing
51-8012	Power Distributors and Dispatchers
51-8091	Chemical Plant and System Operators
51-8092	Gas Plant Operators
51-8093	Petroleum Pump System Operators, Refinery Operators, and Gaugers
51-9011	Chemical Equipment Operators and Tenders
51-9012	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders
51-9021	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders
51-9022	Grinding and Polishing Workers, Hand
51-9023	Mixing and Blending Machine Setters, Operators, and Tenders
51-9031	Cutters and Trimmers, Hand
51-9032	Cutting and Slicing Machine Setters, Operators, and Tenders
51-9041	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders
51-9051	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders
51-9111	Packaging and Filling Machine Operators and Tenders
51-9121	Coating, Painting, and Spraying Machine Setters, Operators, and Tenders
51-9191	Adhesive Bonding Machine Operators and Tenders
51-9192	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders
51-9193	Cooling and Freezing Equipment Operators and Tenders
51-9195	Molders, Shapers, and Casters, Except Metal and Plastic
51-9196	Paper Goods Machine Setters, Operators, and Tenders
51-9197	Tire Builders
53-4013	Rail Yard Engineers, Dinkey Operators, and Hostlers
53-7031	Dredge Operators
53-7032	Excavating and Loading Machine and Dragline Operators
53-7033	Loading Machine Operators, Underground Mining
53-7041	Hoist and Winch Operators
53-7063	Machine Feeders and Offbearers
53-7071	Gas Compressor and Gas Pumping Station Operators
53-7072	Pump Operators, Except Wellhead Pumpers
53-7073	Wellhead Pumpers
53-7111	Mine Shuttle Car Operators

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Appendix B – Additional results

Table B1 – Summary table: definitions and data sources for variables in equation 2

Variable	Definition	Data source
Dummy for areas with local green-manual certifications	Dichotomous variable for CZs organizations granting certificates that are relevant for green-manual occupations in year 2008	Department of Labor, CareerOneStop available at https://www.careeronestop.org/Developers/Data/certifications.asp
Dummy for areas with local nongreen-manual certifications	Dichotomous variable for CZs organizations granting certificates that are relevant for nongreen-manual occupations in year 2008	Department of Labor, CareerOneStop available at https://www.careeronestop.org/Developers/Data/certifications.asp
Share of empl with GGS>p75 (year 2005)	Share of hours worked in 2005 by employees in the CZ of references in occupations with average GGS score above the third quartile of the distribution weighted by hours worked	Hours worked by occupation and CZ: ACS microdata for year 2005, IPUMS; GGS importance (defined in Vona et al., 2018): O*NET database (Occupational Information Network, version 18.0)
Population 2008 (log)	Number of resident people in 2008	Bureau of Economic Analysis
Income per capita (2005)	Average personal income per capita in 2008	Bureau of Economic Analysis
Import penetration (year 2005)	Aggregate (national) ratio between total import and 'domestic use' (import + domestic output – export) by 4-digit NAICS in 2005, attributed to CZ by weighting industry-specific scores with CZ-industry-specific employment share in 2005.	Import and export by 4-digit NAICS: Schott (2008); domestic output by 4-digit NAICS: NBER-CES database; CZ-industry specific employment share: County Business Patterns database
Pre trend (2000-2007) employment tot / pop	Growth in total employment per capita between 2000 and 2007	BLS-QCEW database
Pre trend (2000-2007) empl manufacturing / pop	Growth in manufacturing (NAICS 31-33) employment per capita between 2000 and 2007	BLS-QCEW database
Pre trend (2000-2007) empl constr / pop	Growth in construction (NAICS 23) employment per capita between 2000 and 2007	BLS-QCEW database
Pre trend (2000-2007) empl extractive / pop	Growth in employment in extraction industries (NAICS 21) per capita between 2000 and 2007	BLS-QCEW database
Pre trend (2000-2007) empl public sect / pop	Growth in public sector employment per capita between 2000 and 2007	BLS-QCEW database
Pre trend (2000-2007) unempl / pop	Growth in unemployed per capita between 2000 and 2007	BLS-LAUS database
Pre trend (2000-2007) empl edu health / pop	Growth in employment in education and health (NAICS 61-62) per capita between 2000 and 2007	BLS-QCEW database
Empl manuf 2008 / pop	Manufacturing (NAICS 31-33) employment per capita in 2008	BLS-QCEW database
Empl constr 2008 / pop	Construction (NAICS 23) employment per capita in 2008	BLS-QCEW database
Empl extractive 2008 / pop	Employment in extraction industries (NAICS 21) per capita in 2008	BLS-QCEW database
Empl public sect 2008 / pop	Public sector employment per capita between 2000 and 2007	BLS-QCEW database
Unempl 2008 / pop	Unemployed per capita in 2008	BLS-LAUS database
Empl edu health 2008 / pop	Employment in education and health (NAICS 61-62) per capita in 2008	BLS-QCEW database
Shale gas extraction in CZ	Dummy for local availability of shale gas resources	US Energy Information Administration
Potential for wind energy	Average indicator of potential for wind energy generation (range 1-7)	National Renewable Energy Laboratory
Potential for photovoltaic energy	Average indicator of potential for photovoltaic energy generation (range 1-7)	National Renewable Energy Laboratory
Federal R&D lab	Dummy for CZ hosting R&D lab	-
CZ hosts the state capital	Dummy for CZ hosting a state capital	-
Nonattainment CAA old standards	Dummy for nonattainment status for at least 1/3 of CZ population according NAAQS up to 1997	Environment Protection Agency
Vigintiles of non-green ARRA per capita	Vigintiles of non-green (all agencies and departments except DOE and EPA) ARRA per capita	Recovery.gov
Green employment (O*NET-based) in manual occupations per capita	Average share of hours worked by employees in green-manual occupations weighted by hours worked and occupational greenness, multiplied by total employment in the CZ	American Community Survey data from IPUMS; BLS-QCW database; O*NET 18.0

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Average hourly wage in manual green occupations	Average hourly wage by employees in green-manual occupations weighted by hours worked and occupational greenness	American Community Survey data from IPUMS; O*NET 18.0

Table B2 – Conditional correlations between green ARRA and local green-manual certifications

	(1) Green (EPA+DoE) ARRA per capita (in log)	(2) Green (EPA+DoE) ARRA per capita (in log)	(3) Green (EPA+DoE) ARRA per capita (in log)	(4) Dummy for areas with local green-manual certifications
Dummy for areas with local green-manual certifications	0.235**	0.258***	0.0582	
	(0.108)	(0.0907)	(0.125)	
Share of empl with GGS>p75 (year 2005)			4.273**	2.477**
			(2.084)	(0.979)
Population 2008 (log)			0.0595	0.223***
			(0.0831)	(0.0487)
Income per capita (2005)			-0.0161	-0.00218
			(0.0130)	(0.00856)
Import penetration (year 2005)			-5.196	-2.447
			(10.73)	(4.127)
Pre trend (2000-2007) employment tot / pop			-0.138	-3.501*
			(3.940)	(2.052)
Pre trend (2000-2007) empl manufacturing / pop			-6.998	3.366
			(7.052)	(4.660)
Pre trend (2000-2007) empl constr / pop			-11.12	9.569
			(15.36)	(9.639)
Pre trend (2000-2007) empl extractive / pop			3.993	3.543
			(14.34)	(7.302)
Pre trend (2000-2007) empl public sect / pop			-5.443	9.977
			(8.867)	(7.062)
Pre trend (2000-2007) unempl / pop			3.937	-16.51***
			(15.38)	(5.796)
Pre trend (2000-2007) empl edu health / pop			2.217	-2.295
			(4.897)	(3.453)
Empl manuf 2008 / pop			4.750	1.083
			(2.845)	(1.424)
Empl constr 2008 / pop			48.75***	-7.980*
			(11.10)	(4.286)
Empl extractive 2008 / pop			2.315	4.760
			(8.534)	(3.825)
Empl public sect 2008 / pop			5.258	-2.947
			(7.083)	(2.044)
Unempl 2008 / pop			21.23	8.989*
			(13.25)	(5.111)
Empl edu health 2008 / pop			1.640	-1.917
			(2.241)	(1.792)
Shale gas extraction in CZ			0.265**	0.00696
			(0.128)	(0.0668)
Potential for wind energy			-0.0773	-0.0121
			(0.126)	(0.0507)
Potential for photovoltaic energy			0.125	-0.0101
			(0.0928)	(0.0666)
Federal R&D lab			0.409*	0.213**
			(0.204)	(0.0887)
CZ hosts the state capital			-0.0257	0.127
			(0.193)	(0.0908)
Nonattainment CAA old standards			-0.132	-0.0170
			(0.145)	(0.0809)
US-Division dummies	No	Yes	Yes	Yes
Vigintiles of non-green ARRA per capita	No	Yes	Yes	Yes

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

R squared	0.0118	0.271	0.372	0.559
N	587	587	587	587

OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table B3 – Robustness check: accounting for CZ size as possible moderating factor

Dep var: Change in log outcome variable compared to 2008	(1) Green employment (O*NET-based) in manual occupations per capita	(2) Average hourly wage in manual green occupations
Green ARRA per capita (log) x D2005_2007	0.00119	-0.00697
	(0.00691)	(0.00996)
Green ARRA per capita (log) x D2009_2012	0.00140	0.00548
	(0.00716)	(0.0101)
Green ARRA per capita (log) x D2013_2017	0.0159	0.00383
	(0.00956)	(0.00950)
Green ARRA per capita (log) x	0.0169	-0.0242
Dummy for local green-manual training in 2008 x D2005_2007	(0.0231)	(0.0183)
Green ARRA per capita (log) x	0.0386*	0.0321
Dummy for local green-manual training in 2008 x D2009_2012	(0.0213)	(0.0196)
Green ARRA per capita (log) x	0.0445**	0.0854***
Dummy for local green-manual training in 2008 x D2013_2017	(0.0198)	(0.0181)
Green ARRA per capita (log) x	-0.0130	-0.00998
Dummy for big CZ in 2008 x D2005_2007	(0.0171)	(0.0154)
Green ARRA per capita (log) x	-0.00400	0.0108
Dummy for big CZ in 2008 x D2009_2012	(0.0121)	(0.0134)
Green ARRA per capita (log) x	0.00358	0.0201
Dummy for big CZ in 2008 x D2013_2017	(0.0137)	(0.0158)
Comparison across periods and training:		
- Dummy for local green-manual training = 0		
Green ARRA per capita (log): 2009-2012 vs 2005-2007	0.000208	0.0124
s.e.	(0.0130)	(0.0197)
Green ARRA per capita (log): 2013-2017 vs 2005-2007	0.0147	0.0108
s.e.	(0.0150)	(0.0192)
- Dummy for local green-manual training = 1		
Green ARRA per capita (log): 2009-2012 vs 2005-2007	0.0219	0.0687*
s.e.	(0.0419)	(0.0360)
Green ARRA per capita (log): 2013-2017 vs 2005-2007	0.0423	0.120***
s.e.	(0.0387)	(0.0345)
R squared	0.224	0.241

OLS model weighted by CZ population in 2008. Sample: CZ with at least 25,000 residents in 2008. N of CZ: 587. N of observations: 7631. Standard errors clustered by state in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Year dummies included. Additional control variables (interacted with D2002_2007, D2009_2012 and D2013_2017 dummies): US-Division dummies, Vigintiles of non-green ARRA per capita, Population 2008 (log), Income per capita (2005), Import penetration (year 2005), Pre trend (2000-2007) empl manufacturing / pop, Pre trend (2000-2007) employment tot / pop, Pre trend (2000-2007) empl constr / pop, Pre trend (2000-2007) empl extractive / pop, Pre trend (2000-2007) empl public sect / pop, Pre trend (2000-2007) unempl / pop, Pre trend (2000-2007) empl edu health / pop, Empl manuf 2008 / pop, Empl constr 2008 / pop, Empl extractive 2008 / pop, Empl public sect 2008 / pop, Unempl 2008 / pop, Empl edu health 2008 / pop, Shale gas extraction in CZ interacted with year dummies, Potential for wind energy interacted with year dummies, Potential for photovoltaic energy interacted with year dummies, Federal R&D lab, CZ hosts the state capital, Nonattainment CAA old standards, Nonattainment CAA new standards; dummy for local green-manual training in 2008; dummy for CZ in the top quartile in terms of population in 2008

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Research paper 3: Assessing the social and distributional impacts of ambitious climate policies in Europe with GEM-E3-FIT

Status of the research paper: *The paper will be submitted for review in a top-ranked scientific journal after the submission of the deliverable*

Authors: Panagiotis Fragkos, Kostas Fragkiadakis, Benjamin Sovacool, Zoi Vrontisi, Ioannis Charalampidis, Leonidas Paroussos

Abstract: The implementation of ambitious environmental policies may lead to regressive distributional impacts, disproportionately affecting disadvantaged population groups. In particular, the imposition of additional taxes on energy products may affect negatively the low-income households that face funding scarcity, by increasing the risk of energy poverty. In the current study, the state-of-the-art general equilibrium model GEM-E3-FIT is significantly expanded to represent ten income classes in all EU Member States, by differentiating their income and savings, income sources, and consumption characteristics. We use the new methodological and modelling capabilities of GEM-E3-FIT to quantify the distributional impacts of the EU Green Deal policies and targets, in particular exploring their effects on labour income by skill and on energy and transport-related expenditure by income class. The model-based analysis shows that the transition to climate neutrality may increase modestly the inequality across income classes, with low-income households facing most negative effects. However, using carbon revenues as lump-sum transfers to households and as reduced social security contributions has clear benefits increasing total employment, while reducing significantly the inequality across income classes in European countries.

Keywords: distributional impacts of climate policies, GEM-E3-FIT, income classes, income distribution, inequality, energy poverty

4.1 Introduction

The consideration of distributional impacts in the analysis of energy and climate policies is becoming increasing important as more ambitious policies are implemented worldwide, often imposing taxation on energy products. This was manifested in the recent Yellow vest movement in France, which was marked by mass protests against the rising fuel taxes and claimed that middle and working classes are paying a disproportionate share of the burden from tax reforms. In this context, neglecting the issue of inequality and energy poverty may hinder climate protection action in the EU countries and globally, as increasing levels of income and carbon inequality cause concerns for the sustainability of economic growth and social cohesion.

Ultimately, equity consequences depend on how costs and benefits are initially incurred and how they are shared as per social contracts, national policy, and international agreements. The literature suggests a relation between the effectiveness of cooperative action and the perception of fairness of such arrangements [1, 2]. Thus, topics of equity and fairness have begun to receive a greater amount of attention within the energy and climate literature, namely through the approaches of environmental justice [3], climate

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

justice [4, 5], and energy justice [6]. While such approaches frequently envision justice and equity as an ethical imperative, justice also possesses an instrumental value of enabling deeper and more socially acceptable mitigation efforts [7].

Some equity considerations are closely connected to policies. Depending on the chosen policy instrument and the underlying socio-economic structure, distributional impacts of environmental policies may vary significantly, both within and among countries [8-10]. Overall, literature suggests that environmental policies are usually associated with regressive distributional impacts, disproportionately affecting disadvantaged population groups, in particular low-income classes. There is, however, also evidence for progressive impacts, especially in developing countries where income inequalities can be effectively reduced if targeted policies are implemented [10, 11]. Ignoring possible distributional effects may result in less effective environmental policies and even increased income inequalities potentially leading to energy poverty [11]. Until now, however, most policy impact assessments at the EU and national level do not include a detailed analysis of the policy impact on different socio-economic groups [12]. Monitoring income inequality between and within MSs may shed light on issues such as social cohesion (EC, 2018). However, most of the macroeconomic tools used for policy assessment, do not feature explicit mechanisms to measure inequality. Therefore, it is critical to advance the macroeconomic modelling tools towards that direction by understanding and quantifying the drivers and consequences of income inequality

The assessment of social and distributional impacts of climate policies should consider both financial implications (e.g. impacts on income and wealth distribution and consumption patterns) and potential environmental benefits in the form of reduced climate damages and environmental hazards [13]. The latter is, however, difficult to assess quantitatively, while there is no established robust relationship between low-income and higher exposure to environmental hazards [14]. Therefore, assessments of distributional impacts of climate policies focus on income distribution and consumption, neglecting possible benefits from reduced environmental inequalities.

In the current study, we use the leading multi-sectoral Computable General Equilibrium (CGE) model GEM-E3-FIT, enhanced with a detailed modelling of income deciles, moving beyond the state-of-the-art representing multiple households in the CGE modelling framework. This allows capturing the distributional impacts of energy and climate policies on ten income classes in all EU Member States. In particular, the policy impacts on income distribution and on consumption patterns are consistently estimated, focusing in particular on low-income classes which are more vulnerable to the adverse impacts of climate policies, including inequality and energy poverty. The financial implications (related to income and consumption effects) crucially depend on the policy impacts on labour wages, which are differentiated by production sector, income class and skill level, the households' consumption patterns (e.g. the share of energy-related expenditure in total consumption) and possible budget or credit constraints associated with different disposable income, owned assets, or accessibility to technologies [10]. These factors are consistently captured in the GEM-E3-FIT modelling framework that allows the evaluation of the threat of income inequality and energy or technology poverty, for each EU Member State (MS) and each income class dynamically over 2020-2050.

Depending on how the climate policy is funded, which sectors, jobs and labour skills are impacted and who consumes the affected goods, policy effects may differ per household type and income class. The GEM-E3-FIT model is used to assess policy instruments that aim at alleviating the adverse social effects for low-income households,

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

but considering budget neutrality to ensure comparability of alternative policy scenarios. It is clear that well-designed policies and strategies may reduce income inequality and energy poverty by considering appropriate compensation schemes, either by increasing household income through lump-sum payments or reducing other taxes, or by public investments, e.g., in infrastructure, or through the social security system [9-11]. Through comprehensive model-based analysis, alternative policy options are explored to minimise adverse distributional and social impacts of the "optimal" EU emission reduction pathway and required adjustments are proposed in order to render the pathway more acceptable and manageable in the EU, especially focusing on low-income classes.

The remainder of the study is structured as follows: Section 2 presents an overview of the policy context and related literature on distributional effects of climate policies, focusing on income inequality and energy poverty. Section 3 introduces the GEM-E3-FIT modelling tool used in the study and the methodological advancements to represent income deciles. Section 4 presents the key socio-economic and distributional impacts of ambitious climate policies across EU countries and income classes. Section 5 introduces the main policy-related implications, while Section 6 concludes.

4.2 Background and Literature Review

Given both the importance of the topic, but also the diverse perspectives taken by different research communities, a plethora of relevant research has emerged over the past few decades looking broadly at issues of equality, poverty, and policy. This section summarizes six distinct research themes.

4.2.1 Income inequality: definition and indicators

Rising income inequality is a global concern, implying that economic growth is not inclusive and its benefits are not equally distributed to all households [15]. Income inequality can reduce economic growth and aggregate demand, as those on high incomes typically have a lower marginal propensity to consume [16, 17], while it raises concerns about sustainable growth as the gap between rich and poor widens [18].

Income inequality is defined as inequality in earnings received from employment (wages, salaries, bonuses, self-employment earnings), private income from investments and property, transfers between households, state benefits, pensions and rent [19]. Income inequality describes the gap between the rich and poor segments of society and is often measured through households' disposable income. The standard representation of household income in GEM-E3-FIT is through a single "representative" household in each region that averages incomes and consumption patterns. This approach assumes that all forms of income, both from primary resources (i.e. labour and capital ownership) and institutional transfers (pensions, property income, interest rates, foreign transfers, etc.), are allocated to a single representative household, thus not allowing for an assessment of policy impacts on different households within a country.

The drivers of income inequality are widely discussed in the literature. A comprehensive review on drivers of income inequality is included in [20]:

- Changes in labour market, which directly impact unemployment and the distribution of wages. Part-time and temporary employment negatively impact income inequality,

"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"

which is reinforced by the gender gap in wages and high unemployment of younger generations [21]. The increased flexibility of the labour markets poses challenges for workers, especially those with low skills, who are commonly the first to be substituted, thus worsening income inequality.

- Labour institutions, which may lead to reduced wage dispersion, but they can also result in higher unemployment [20]. Literature findings show that trade union membership and days of maternity leave have a positive effect on income distribution.
- Technological change, which increases productivity and well-being, but also requires higher skilled labour thus contributing to increased inequality, in case that the pace of technological change is higher than the pace of educational development. Technology progress driven by digitisation and automation changes occupational structures which affects income inequality through replacement of routine-based jobs [22].
- Globalisation. Trade is an engine for economic growth as it increases competitiveness and efficiency, but trade globalisation tends to widen the income gap [20]. Trade openness could negatively impact the wages of unskilled labour in developed economies where firms can easily outsource production. The overall impact of trade on inequality is hard to assess as this is largely influenced by country differences in labour capacity and productivity [20].
- Financial Globalisation effects on equality are mixed. It can have a positive effect on inequality as it facilitates efficient international allocation of capital. On the other hand, Foreign Direct Investments are mostly allocated in funds supporting technology development, increasing demand for high-skilled workers, leading to higher income inequality [23]. Moreover, a global financial crisis disproportionately affects low-income households, increasing unemployment rate and income inequality [24].
- Education determines occupational choice, access to jobs and the level of wages [25]. The impact of education on inequality depends on the size of education investments by individuals and governments and the rate of return on these investments [20].
- Redistributive policies: Tax and transfer systems play a major role in income equality as it is estimated that transfers account for 75% of the average reduction in inequality across OECD, but with wide variations across countries, depending on the size and progressivity of transfers. The personal income tax tends to be progressive, while social security contributions and consumption taxes tend to be regressive. Thus, the redistribution of income is best done through personal income taxes and targeted transfers to poor households [26].
- The household's composition and ageing population drive income inequality, with single-person households often experiencing higher inequality, as there is no capacity to poo resources. The ageing population changes households' composition (lower number of members and higher housing costs) and increases pressure on the social welfare system [27].
- Wealth. The distribution of wealth has a negative effect on income inequality as return on capital are large source of households' income [28, 29]. Studies show differences in saving behaviour across income classes, with higher income households saving a larger fraction of their income. [30] shows that the lower and middle incomes are not able to keep pace with housing prices.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Most of these drivers are featured in GEM-E3-FIT modelling framework and thus the model can endogenously assess income inequality in policy scenario assessments. In particular, GEM-E3-FIT model includes:

- a detailed representation of the labour market with endogenous involuntary unemployment for 5 different occupation and skill types;
- endogenous technological change through learning by doing and learning by R&D, particularly for low-carbon technologies;
- a detailed representation of ten income classes through multiple households;
- endogenous bilateral trade of goods and services;
- an endogenous representation of human capital development and the decision of households for education enabling an upgrade of skills;
- a detailed representation of direct and indirect taxes, subsidies and other benefits.

The table below includes the most common indicators used to measure income inequality. The Gini coefficient is the most established and popular indicator, while the decile dispersion ratio presents the ratio of the average income, for instance of the richest 10 percent of the population to the poorest 10 percent [31]. However, this indicator does not use information about the distribution of income within deciles and does not provide information about incomes in the middle of the distribution. Other indicators have been developed to improve the understanding about income distribution, e.g. Generalised Entropy family (e.g. the Theil index) and the Atkinson index which allow to examine the effects of inequalities in different sub-regions of the income spectrum enabling enhanced assessments of different inequalities.

Table 7: Indicators to measure income inequality

Indicator	**Description/ relevance for inequality**
Mean and median income by household	The mean income is the amount obtained by dividing the total aggregate income of a group by the number of units. The median is the income level that divides the population into two groups of equal size. The use of the median corrects potential distortion that may be caused by the existence of extreme values.
Decile dispersion ratio	This measure presents the ratio of the average income of e.g. the richest 10 percent of the population divided by the average income of the poorest 10 percent [31]. The indicator is vulnerable to extreme values and outliers.
S80/S20 income quintile share ratio or 20:20 ratio	Comparing the income received by the top 20% of the population with the bottom 20% of the population.
Gini coefficient	The Gini coefficient is based on the Lorenz curve, a cumulative frequency curve that compares the distribution of income with the uniform distribution that represents equality. It represents the extent to which the distribution of income differs between an equal distribution (Gini coefficient of 0) and perfect inequality (Gini coefficient of 1). It is sensitive to income differences around the centre of distribution.
Atkinson index	This index is based on the Gini index and includes a sensitivity parameter, which can range from 0 (meaning indifference about the nature of the income distribution), to infinity (where the focus is on the lowest income group) [32].

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

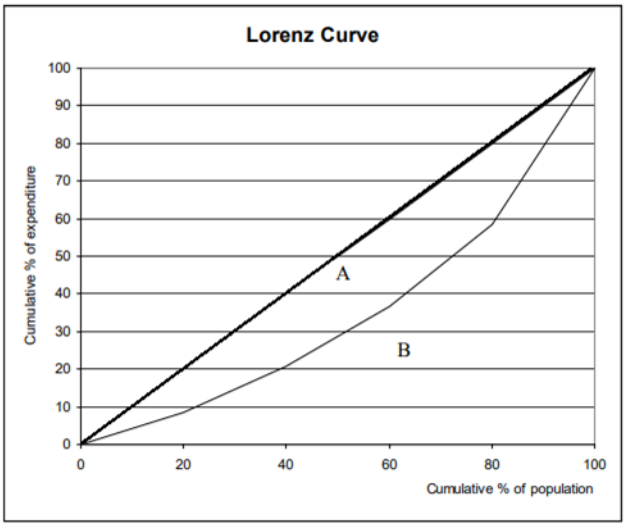
At risk poverty rate	The share of people with an equivalised disposable income below the at-risk-of-poverty threshold, which is set at 60% of the national median equivalised disposable income [33].
Severely and materially deprived	It reflects the inability of a household to afford some goods and services considered to be necessary for an adequate life [33]. The indicator measures the share of population that cannot afford three (material deprivation) or four (severe material deprivation) of the nine items listed in a reference year.

The advanced GEM-E3-FIT model will estimate income inequality by simulating households by income decile (i.e. dividing the household population into deciles that are depicted by 10 representative households or equal-sized household groups). The analysis of distributional impacts and income inequality focuses on the income changes between deciles. The indicators of income inequality can be estimated using a combination of modelling results, additional income data, and supporting assumptions, outside the model. The study focuses on quantifying the inequality indicators using modelling results, including the Gini coefficient and the Decile Dispersion ratio (S80/S20). These indicators complement each other; for example, the Gini coefficient is particularly sensitive to income differences around the centre of the distribution and thus it should be used in combination with the S80/S20 ratio as the ratio gives information about the distribution between the lower and upper deciles. The literature suggests to use both income and expenditure measures in order to get a multidimensional poverty profile across and within EU Member States [34].

The **Gini coefficient** is estimated by calculating the area between the Lorenz curve and the cumulative population axis. The Gini coefficient is defined as follows: A/(A+B), where A and B are the areas above and below the Lorenz curve respectively as shown in the Figure below. As the analysis is implemented at the decile level, the entire Lorenz curve is not known and is approximated with interpolation between the decile points, based on the assumption that income is distributed equally within each decile. Given the use of linear interpolation, the area underneath the Lorenz curve can be broken down into a series of rectangles and triangles. If income data is available at a more granular level (e.g. by percentile), the Lorenz curve can be more precisely defined. Using results by income decline provides less information about the income distribution, as the variance within the deciles is not considered. Overall, the changes in within-group inequality are not measured in GEM-E3-FIT, thus losing information on total inequalities and inter-group income disparities. The **Atkinson index** can be calculated using results from GEM-E3-FIT model, as it uses the same parameters as the Gini coefficient, while additionally the sensitivity value should be defined.**Error! Reference source not found.**

Figure 1: Lorenz curve. Source: World Bank (2005)

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*



The S80/S20 ratio compares the average income received by the top 20% of the population with the bottom 20% of the population. The ratio can be calculated as follows:

$$S80/S20_{Country} = \frac{Income_{Top\ 20\%}}{Income_{Bottom\ 20\%}}$$

where:

$Income_{Top\ 20\%}$ represents the sum of the equivalised disposable income of the top 20% of the population.

$Income_{Bottom\ 20\%}$ is the sum of the equivalised disposable income of the bottom 20% of the population.

This indicator can be quantified using directly the GEM-E3-FIT model results for income deciles.

4.2.2 Past and current developments of income inequality

In the last 25 years, extreme poverty and income inequality has decreased globally [35]. While global inequality remains high, after 2000 inequality started to decline (Figure 2), largely induced by the decrease of inequality between countries [35].

Inequality varies greatly among regions. In 2017, the richest 10% earned only 37% of total income in Europe [37], while this share was even higher in China, Russia, the US and Canada, ranging between 41% and 47%. In Sub-Saharan Africa, Brazil, India and the Middle EST the share was 55-61% of income [37]. From 1980, income inequality increased moderately in Europe and more rapidly in North America, China, India and Russia. The diversity of trends across countries shows that a variety of national, institutional and political contexts influence the dynamics of income inequality (Figure 3). The spread from the most unequal countries in Latin America and Sub-Saharan Africa, to the lowest-inequality in some EU countries is very high.

Figure 2: Gini coefficient overtime for the world, 1980–2016, Source: [36]

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

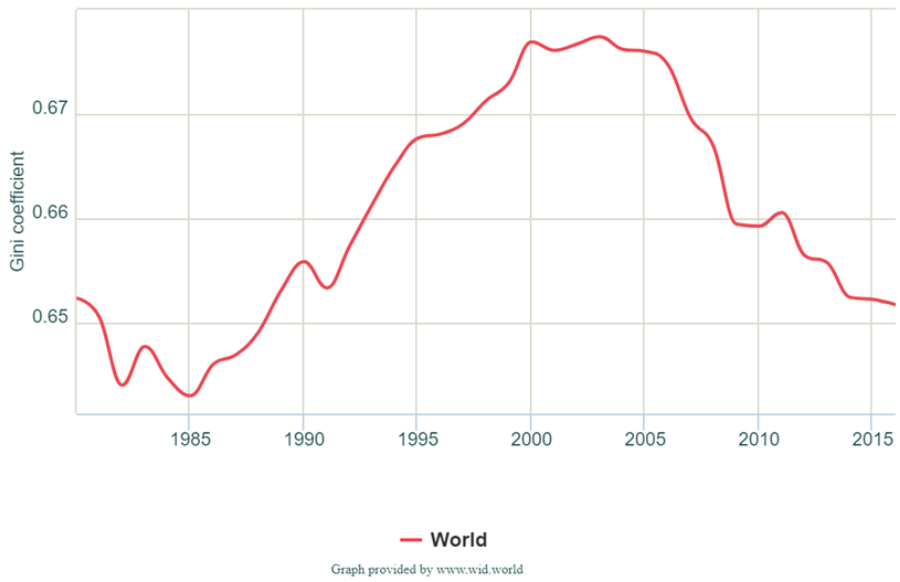
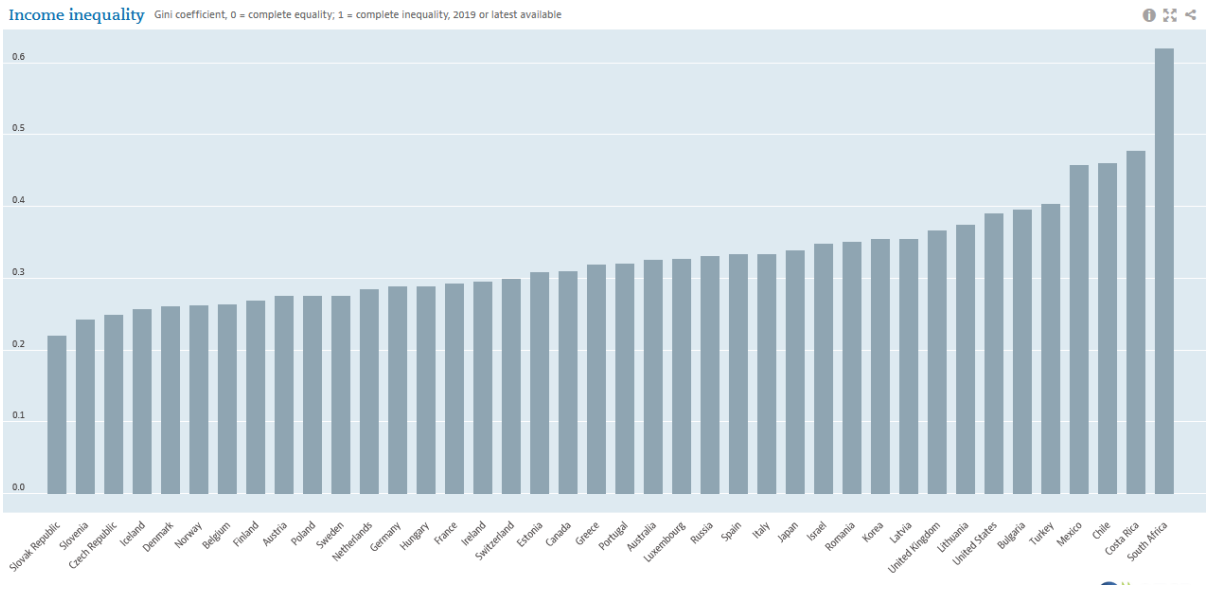


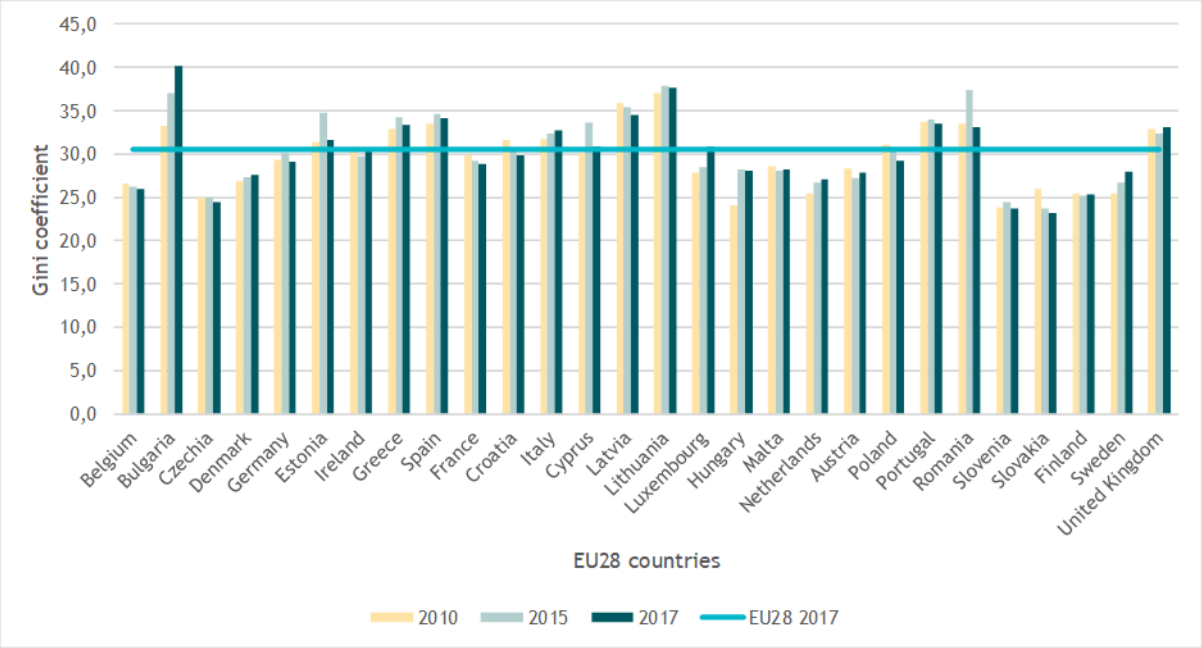
Figure 3: Gini coefficient in various countries in 2018, Source: OECD data, 2020



In 2017, the Gini coefficient for the EU-28 was 30.6, compared to 30.5 in 2010, indicating that income inequality in the EU-28 has remained stable after 2010. The Gini coefficient was the highest (above 35.0) for Bulgaria and Lithuania, while the lowest income inequality in the EU-28 is observed in Belgium, Finland, the Czech Republic, Slovenia and Slovakia [33].

Figure 4: Gini coefficient of equivalised disposable income (ilc_di12). Source: Eurostat

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*



While the Gini coefficient illustrates how far away the distribution of income is from a perfect equal society, the S20/S80 income ratio provides insights on the allocation of income in the richest and poorest 20% of households. In 2017, the EU-28 S80/S20 ratio was 5.08, implying that the richest 20% of the population receives five times higher income relative to the poorest 20%. This share has increased moderately by 0.4% per year over 2010-2017, indicating a small increase in inequality. The highest ratio was recorded in Bulgaria (8.2) and the lowest ratio was 3.4 in Czech Republic and Slovenia. In 2017, the poorest 20% of the European population received less than 8% of the total disposable income, while the richest 20% accounted for 41% of the total income.

The statistical analysis reveals that the lower deciles have experienced the largest income losses in the last decade as the economic crisis and government austerity measures across many EU Member States disproportionally affected low income groups [38]. Social transfers (pensions, unemployment and other benefits, housing allowances, social assistance and tax rebates) reduce income inequality and have a significant effect on European welfare systems, as illustrated by the comparison of Gini coefficients before and after social transfers. In 2018, the EU-28 Gini coefficient before social transfers was 51.1, which drops to 30.8 after social transfers. These effects are even larger in Sweden, Germany, Greece and Portugal, with a decrease of more than 25 points [33].

4.2.3 Energy poverty: definition and indicators

Energy poverty is described as the lack of access to adequate energy services at an affordable cost. It is a problem across many EU Member States, as around 50 million people are estimated to be affected by energy poverty [39] and are excluded from the benefits of the energy transition and integrated energy market. In this context, energy poverty is increasingly becoming an important issue in the European and national policy

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

agenda. The Energy Union Strategy[17] explicitly recognizes the challenge, stating that energy poverty negatively affects living conditions and health.

Due to the diverse energy policy contexts of EU countries, there is no common definition of energy poverty across the EU and several definitions of energy poverty exist in the literature. A list of energy poverty definitions considered across Member States is presented in [40]. Overall, households that "experience inadequate levels of essential energy services (i.e. heating, cooling, lighting, fuels for transport), due high energy expenditure, low household incomes, inefficient buildings and appliances, and specific household needs" are classified as energy poor.

A combination of energy-inefficient housing and appliances, high energy prices and low income levels determine if a household is at risk of energy poverty [41, 42]. However, there are many drivers and factors that can influence the dynamics of energy poverty, with multiple linkages between them. The household energy system, including energy service demands, energy uses and resulting expenditure of a household, is at the core of the energy poverty. The study [40] identified six categories of drivers that impact the affordability of adequate household energy services, and may potentially lead to energy poverty namely: Physical infrastructure, Climate, Socio-demographics, State of the economy, Income, Energy market and prices.

Two main approaches are identified in the literature to assess energy poverty: Expenditure-based and Consensual-based. The former defines energy poverty based on information about household's expenditure in energy, often compared to the household's income and uses a threshold beyond which a household is classified as energy poor [43]. Consensual self-reported metrics identify households that declare to face difficulties to meet basic energy services ("perceived deprivation"). These metrics are commonly used in energy poverty analyses due the availability of the consistent EU-SILC survey across Europe [43]. The two approaches have different strengths and weaknesses and can thus be used in combination. For instance, expenditure-based metrics may consistently quantify required energy expenditure, but do not reflect consumers' motivation for expenditure levels given budget constraints. Consensual-based metrics can capture wider elements of energy poverty and are easier to implement, but they are highly subjective and difficult to compare across Member States.

The current study focuses on expenditure-based indicators that can be quantified using GEM-E3-FIT model outcomes on energy expenditure and income per decile, in particular: High share of energy expenditure in income (2M). This indicator measures the proportion of households whose share of energy expenditure relative to its disposable income is more than twice as large as the national median share. The highest income group has a very low percentage of households in energy poverty [40], as the richer a household is, the lower the average share of income dedicated to energy expenditure. As noted by the Energy Poverty Observatory, in countries with less income inequality, variance in energy expenditure results in a higher share of households in energy poverty (based on 2M index). To calculate the energy poor threshold determining whether a household is in energy poverty or not, we use the following formula:

$$\% \ \frac{Energy\ expenditure_{hh}}{Disposable\ income_{hh}} \geq 2 * \mathrm{M(ENEXShr)}_{Country}$$

where:

[17] COM (2015) 80 A Framework Strategy for a Resilient Energy Union with Forward-Looking Climate Change Policy

"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"

$Energy\ expenditure_{hh}$ represents the sum of the reported household's energy expenses, covering payments for energy fuels and services
$Disposable\ income_{hh}$: the reported household's equivalised disposable income (the household's income minus taxes),
$\mathrm{M(ENEXShr)}_{Country}$: the national statistical median of the share of energy expenditure relative to disposable income.

4.2.4 Past and current developments of energy poverty

The analysis of energy poverty indicators at EU level shows a downward trend on the percentage of population being unable to keep their homes adequately warm over 2010-2017. In 2017, Bulgaria has the highest share of population that reported not being able to keep their home adequately warm (36.5%) followed by Lithuania (29%), Greece (26%), Cyprus (22.9%) and Portugal (20.4%). The latest data available for calculating the shares of energy expenditure in income dates back to 2010. The highest proportion of households whose share of energy expenditure in income is more than twice the national median share is estimated at 21.4% for Lithuania, followed by Romania (18.6%), while the Netherlands was reportedly the MS with the lowest 2M indicator (6.5%).

The Energy Poverty Observatory analysis reveals that different indicators show different energy poverty dynamics across EU countries, as indicators measure different dimensions of energy poverty. Some indicators may not be as useful as others for certain countries and should be combined with additional nationally relevant indicators. The Energy Poverty Observatory has not developed a composite energy poverty indicator. Other approaches like the European Energy Poverty Index (EEPI) combine different metrics into one single indicator used to assess and track progress made by EU Member States in alleviating energy and transport poverty [44].

4.2.5 Modelling income inequality and energy poverty

CGE and macro-econometric models, enhanced with a representation of different socio-economic groups (e.g. income classes) can be used to evaluate the distributional implications of climate policies. The representation of different households and labour types determines the level of detail in inequality analysis. For instance, disaggregation by skill group, gender, age and income class are relevant for distributional analysis about income and consumption. Introducing heterogeneity in models is challenging due the complex interlinkage between growth and inequality [45]. The introduction of additional households enhances the capability of conventional macro-economic models to assess income distribution effects [46] and can be implemented through the simulation of multiple households (e.g. based on income or occupation) or via micro-simulation where labour supply is modelled at the lowest possible aggregation level.

Conventional CGE models represent one "representative" household, which aggregates all households of the region and is assumed to maximize its utility according to its consumption preferences. For example, the conventional GEM-E3 model version assumes that households maximise their welfare and choose the optimal allocation of consumption to different purposes. Welfare maximization is derived from the decision for education so as to maximise intertemporal income, the decision of income allocation between consumption and savings, and finally the decision on allocating the consumption

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

over different consumption categories. The model features a distinction between durable and disposable goods and services, allowing also for “linked” consumption of disposable goods (e.g. fuels) for the operation of certain durable goods (e.g. vehicles). In the model, the disposable income is formulated by the earnings from labour and capital ownership after taxes and by other income sources (e.g. social benefits). The household decides on the allocation of its consumption over different consumption categories (COICOP) by maximising a Linear Expenditure demand system subject to its disposable income not used for obliged consumption (subsistence minima consumption).

The representation of multiple households in applied CGE modelling has been long established [47, 48, 49] but it is usually constrained by data availability. There are different ways to differentiate households, but income class is the most relevant for distributional analysis. The main caveat of this approach is that it does not capture that households can switch deciles and different household compositions [50]. Occupation, household composition and skill level can also be used to differentiate households. [51] proposed a CGE with six representative households: rural, small landowner, large landowner, urban low-education, urban high-education and capitalist, to address income distribution and poverty. [47] accounted for intra-category variation by assuming a beta or lognormal distribution of income within each representative household using base year data. In this approach, the CGE provides the change in average income per representative household and its variance within household categories is assumed to be fixed.

Microsimulation modelling represents individual households using household microdata. This approach is especially relevant for distributional analysis across different dimensions, including income class, household composition, age etc. Microsimulation allows to explore policies that affect specific households thus providing flexibility [50].The incorporation of full household survey data into modelling faces challenges, as these surveys commonly cover tens of thousands of individual households. CGEs can be linked to microsimulation models to estimate the distributional impacts of policies in Nepal [47] France [52] and Australia [46].

Microsimulation models can be either "static" or "dynamic", where the latter can account for changes at the household level, e.g. child birth, new job, retirement, and thus they are able to produce more realistic long-range estimates [53]. Microsimulation models can use behavioural equations to capture the changes in behaviour of individuals in response to changes in policies and/or prices. By linking CGE and microsimulation models, it is possible to capture endogenous responses throughout the economy, while capturing impacts across the income distribution and on poverty.

4.3 Methodology

4.3.1 The GEM-E3-FIT modelling framework

4.3.1.1 *General Features*

The GEM-E3-FIT model is a multiregional, multi-sectoral, recursive dynamic CGE model, which provides details on the macro-economy and its complex interactions with the environment and the energy system. In the current study, GEM-E3-FIT has been enhanced with a representation of ten income classes aiming to assess the distributional implications of climate policies based on quantifying the indicators presented above. GEM-E3-FIT simultaneously represents 46 regions (including the EU Member States

*“This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Grant Agreement No **730403**“*

separately) and 53 activities linked through endogenous bilateral trade flows and runs until 2050 with a 5-year time step. It covers the interlinkages between productive sectors, consumption, price formation of commodities, labour and capital, bilateral trade and investment dynamics. GEM-E3-FIT formulates the supply and demand behaviour of economic agents who are assumed to exhibit optimising behaviour while market derived prices are adjusted to clear markets. The model is dynamic, recursive over time, driven by accumulation of capital and knowledge, features alternative market regimes, equilibrium unemployment, energy efficiency standards, carbon pricing and can quantify the socio-economic and distributional impacts of policies. GEM-E3-FIT allows for a consistent comparative analysis of policy scenarios since it ensures that in all scenarios, the economic system remains in general equilibrium.

Industries operate within a perfect competition market regime and maximize profits, considering the possibilities of input substitutions between capital, labour, energy and materials. Households' demand, savings and labour supply are derived from utility maximization using a linear expenditure system (LES) formulation. Households receive income from labour supply and from holding shares in companies. Investment by sector is dynamic depending on adaptive anticipation of capital return and activity growth by sector. A distinctive feature of GEM-E3-FIT is the representation of imperfect labour markets through involuntary unemployment, simulated by an empirical labour supply equation that links wages and unemployment levels for five labour skills.

The model endogenously formulates production technologies allowing for price-driven estimation of intermediate consumption and the services from capital and labour. In the electricity sector, a bottom-up approach is adopted to represent thirteen different power producing technologies. For the demand-side, the model formulates consumer behaviour and distinguishes between durable (equipment) and consumable goods and services. GEM-E3-FIT is calibrated using GTAP dataset and national input-output tables that provide a self-consistent accounting of households' consumption, firms' production structures, trade, gross fixed capital formation and sectoral value added.

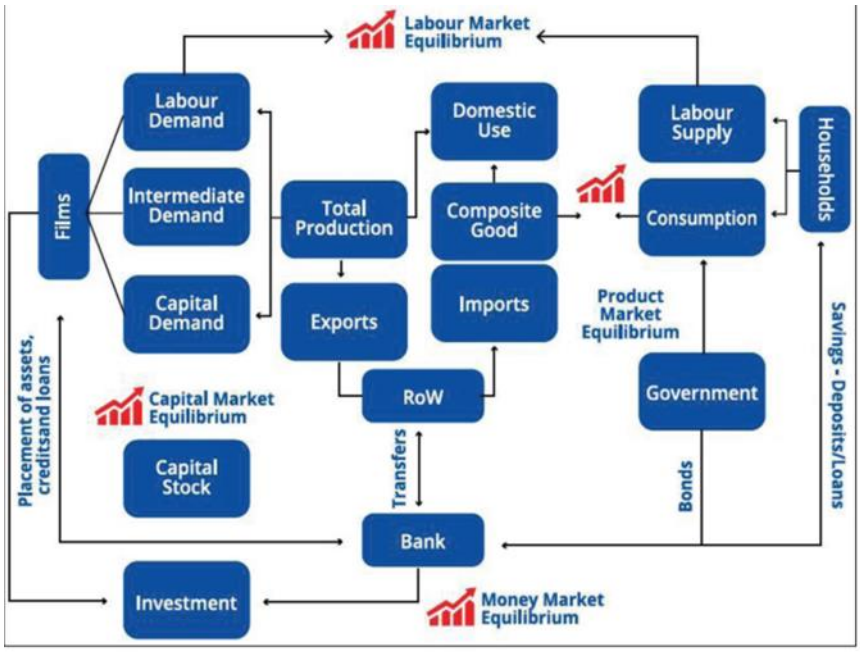
GEM-E3-FIT model includes several features that go beyond a conventional CGE approach, allowing for an improved representation of the policy impacts on the economy and the society (Figure 5). In this respect, it incorporates: a detailed representation of the financial sector, endogenous growth through R&D and learning-by-doing for low-carbon technologies, detailed modelling of energy system and technologies and representation of employment by skill. Additional details on the GEM-E3-FIT model features can be found in INNOPATHS Deliverable D4.1 (which is publicly available in https://innopaths.eu)

Various policy instruments can be represented in GEM-E3-FIT model, which has been extensively used for policy analysis by the European Commission, World Bank and various government agencies [54, 55]. The model focuses on analysing energy and climate policy measures, but also their interactions with other policies related to labour market, economy, industry, trade and innovation. Policies are analysed as counterfactual dynamic scenarios and are compared against the Reference scenario representing Business as Usual trends. Policies are then evaluated through their impact on sectoral growth, income distribution, employment, economic competitiveness and welfare. GEM-E3-FIT can assess the impacts of market-oriented policy instruments, such as carbon taxes and pollution permits and investigates market-driven structural changes, in order to maximize policy efficiency and alleviate adverse distributional effects both among and within countries. The model can analyse different burden sharing schemes over different countries and their effects in the allocation of capital, income, trade and labour in order

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

to define compensating measures aiming at alleviating negative impacts on vulnerable regions and income classes.

Figure 5: GEM-E3-FIT model structure



4.3.1.2 *Modelling income classes in GEM-E3-FIT*

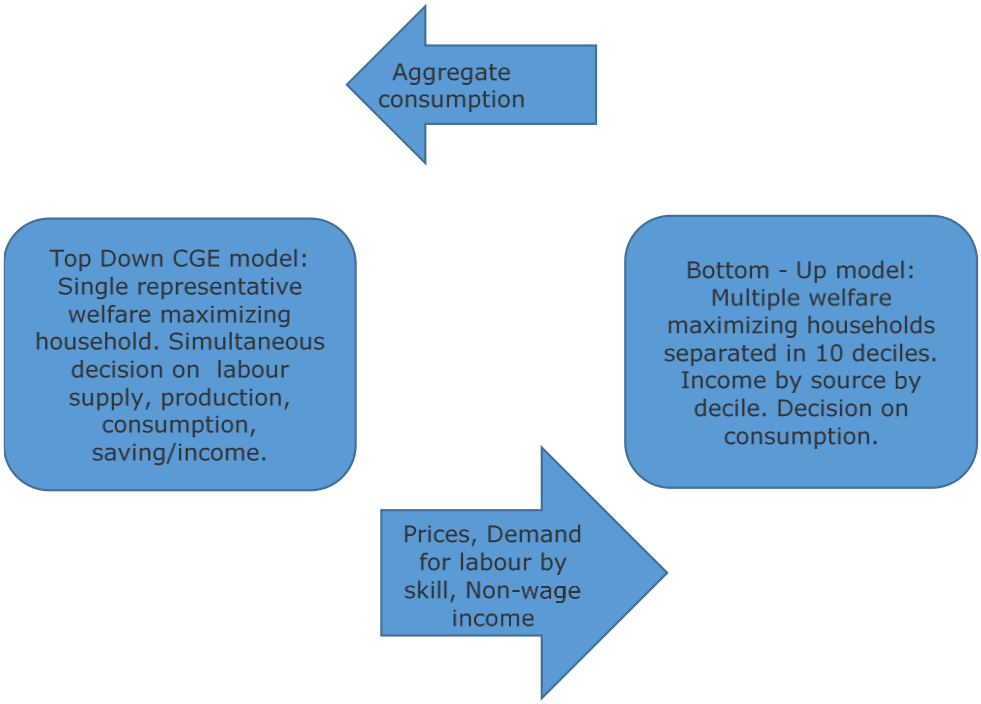
The representation of multiple households in CGE models is a challenging task both from a computational and data point of view [46]. Two main approaches are used to represent multiple households in the CGE framework:

a) **Hard link**: Integration of many representative households to the CGE model where all consumption and production decisions are taken simultaneously [56, 57]
b) **Sequential - Soft link**: A CGE model with single representative consumer is linked with a satellite module with multiple households, through a sequential exchange of prices, incomes and demands until an equilibrium point is established [58, 59].

The hard link approach offers internal consistency and allows for capturing the feedback effects but suffers from computational complexity, while the soft-link approach is easier to implement with manageable computational complexity and it is thus adopted in GEM-E3-FIT. This decision was driven by the empirical findings of [58] who showed very limited benefits from using the hard link representation as compared to the sequential approach, as the second order effects are small. Considering the large size of the model representing 53 economic activities and 46 countries, the need for short model running time and the limited regional coverage of household budget surveys has driven our selection of the soft link approach to represent multiple households in GEM-E3-FIT (Figure 6).

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Figure 6: Methodology to model multiple households in GEM-E3-FIT



The Bottom Up model (BU) is first calibrated using the aggregate consumption, wage and non-wage income, population and labour demand and supply of the Top down (TD) CGE model and the distribution by decile (that is described below). Then, the TD model projects total income, sectoral production, unit production costs, end-user prices and demand for skills until 2050. Total wage and non-wage income, transfers, prices of goods and services, wages by skill and skill requirements are passed on to the BU model in order to compute income and consumption for income deciles, and estimate the impacts on different households including changes in labour income and skill requirements. The next step is the aggregation of individual consumption to the single representative household and plug this in to the TD model where a new set of prices and wages will be computed, ensuring that the economy is in an equilibrium, where demand is covered by supply. This loop continues until the change in prices and demand for products is below a certain threshold ensuring general equilibrium.

In the BU model households are aggregated to 10 income classes with different consumption and saving patterns and different sources of income. It is assumed that the equivalized household size by decile and the type of labour skills supplied by each decile remain constant over time. The link between skills, sectoral activity and income deciles depends on the skills acquired by each household in the base year and the evolution of sectoral production. As explained in Section 2, the analysis of distributional impacts such as energy poverty may require a finer resolution of individual households which is not captured by the decile representation. To do so ex-post calculations can be implemented using truncated normal distributions of households within each decile.

4.3.1.3 *Estimating income inequality and energy poverty indicators in GEM-E3-FIT*

The equivalised disposable income by decile is used to calculate income inequality indicators, but GEM-E3-FIT produces total disposable income by decile. The estimation of the equivalized disposable income from model results can be implemented

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

by assuming that the equivalised household size by decile remains constant over 2015-2050 combined with a simplified assumption about the number of households by decile.

The GEM-E3-FIT results on income by decile can be used to quantify the Gini coefficient, by estimating 10 points of the Lorenz curve, each one representing an income decile group. The area under the Lorenz curve can be calculated by summing the areas of the 10 trapeziums allowing to estimate the Gini coefficient as equal to the area below the line of perfect equality minus the area calculated below the Lorenz curve divided by the area below the line of perfect equality (0.5).

The decile dispersion indicators can be directly estimated via the income by decile quantified by GEM-E3-FIT. A number of decile dispersion indicators will be calculated to allow for a comprehensive evaluation in the tails and in the middle of the distribution. The S80/S20 ratio compares the income received by the top 20% of the population with the bottom 20% of the population. The disposable income of the last two and first two decile groups is utilised to calculate the S80/S20 indicator using GEM-E3-FIT results.

The indicator "share of energy expenditure in income (2M)" is used to identify energy poverty in low-income households and can be estimated by using the decile's total energy expenditure and the total equivalised disposable income. However, this indicator also requires information on the distribution of absolute energy expenditures and incomes on household level to derive changing median values that serve as the threshold for the indicator. The GEM-E3-FIT model cannot provide the median of the share of energy expenditure to disposable income and thus only an adjusted 2M indicator can be estimated using the model output. A simplified approach is based on the comparison with average share of energy expenditure of middle deciles, i.e. D5 and D6. The alternative option to estimate energy poverty using GEM-E3-FIT output is to calculate the average shares of energy expenditure in income by income decile. While this approach does not reflect the relative burden on individual households in relation to national circumstances and the unequal distributions within a decile, it provides insights regarding the economic burden of the energy-related expenses on household budgets. Thus, this indicator will be used in the analysis of distributional impacts.

4.3.1.4 *Data requirements*

In order to go beyond a single representative household, it is necessary to use household level data for empirical grounding. Data needs for modelling include:

- Disaggregating household expenditure by product categories and income class
- Disaggregating household earnings by branch and income class
- Data for calculating Expenditure-based energy poverty indicators

Two key data sources are used, the EU Survey on Income and Living Conditions (SILC) and the Household Budget Survey (HBS). Both datasets provide relevant information to characterise the different households but have methodological differences; the EU-SILC largely focuses of income data at EU level, while the HBS comprises data on household consumption expenditures. HBS and SILC data are based on different samples and cannot easily be matched, as income data of both datasets vary considerably. Finally, SILC data is harmonised across EU countries by Eurostat, while the HBS data are gathered by national statistical offices in a partially harmonised manner, while not ensuring comparability between countries. We use SILC data for disaggregating income sources and HBS data for detailing household consumption and calculating expenditure-

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

based energy poverty indicators (e.g. share of energy-related expenditures on households' disposable income). Income and expenditure disaggregation are based on the micro data on an average per-household level and per income decile and are then used in the modelling together with population data to ensure consistency. Data for each MS and for each income decile is extracted from the SILC and HBS microdata for the latest available year. In particular, data are gathered for structure of population (e.g. number and size of households, occupation), income (income sources per occupation, benefits, transfers, allowances, Dividends and property income, saving rates), Expenditures (taxes, transfers, Consumption per purpose) and indicators on energy poverty and income inequality.

Data from the HBS database include average household expenditures for different consumption categories and total consumption by decile. Income deciles by country are constructed using national household sample weights included in the HBS dataset and each household in the dataset is assigned to a decile. Subsequently, average expenditures of households within each decile by COICOP category are calculated, using sample weights to obtain the actual distribution in the population. For energy expenditure and net income, standard deviations and skewness by income decile are calculated in the same way. To calculate the average share of energy expenditure in households' income by decile, household energy expenditures are divided by incomes. Then, weighted averages, standard deviations and skewness by country and income decile were calculated, using household sample weights. Each household, whose share of energy expenditure in income exceeds the specified median threshold is coded as energy poor, enabling the estimation of the share of energy poor households by decile.

As expected, the HBS data face data gaps and poor quality, with several countries providing no or incomplete expenditure data for some consumption categories or limited data on household incomes (e.g. Italy). To ensure a comprehensive coverage of all EU countries, we imputed data from other countries with similar macro-economic indicators, Gini coefficients and geographical location. As total expenditure does not always match the aggregated value of expenditure across COICOP categories, the disaggregation by income decile of the cumulated values across COICOP is utilised.

The data requirements from the SILC data base mainly relate to disaggregations of household income, number of households by household size, occupation and transfer payments. These data are used to inform the disaggregation of a single representative household into 10 households differing in income with empirical data by income decile. The calculation of average household by income decile is straightforward based on the same approach used for HBS data above. In addition to the average per-household data (by country and decile), data for other variables are extracted: total gross and disposable incomes, decile-specific top cut-off points, standard deviations, skewness, income per occupation (ISCO-88), tax payments, income from other sources: various household and personal-level benefits and transfers, interests, properties, pensions.

Two key data-related challenges have emerged: The first relates to data structure that represents how individuals are nested in households, while GEM-E3-FIT represents only household income, which is estimated based on individual and household-level in- and outgoing payments (some guidelines are provided by Eurostat). As household-level information is key to macro-economic modelling, we assigned household-level income deciles to individuals for calculating resulting per-capita averages and per-decile totals. For most variables, macro-level data published by Eurostat cannot be replicated and thus are only used for calibrating model-endogenous totals to the respective shares.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

4.3.2 Scenarios explored

The study aims to assess the distributional implications of ambitious energy and climate policies focusing on low-income households. The implementation of the EU Green Deal targets and its long-term climate neutrality strategy would lead to different distributional impacts on income classes, potentially increasing the risk of energy poverty for low-income households. The sections below provide detailed descriptions of the alternative scenarios analysed.

4.3.2.1 *The Reference scenario*

The Reference scenario is a projection for the global economic and energy system evolution based on historical and current trends, a wide range of exogenous assumptions and scientific expertise on specific fields. It represents the benchmark against which alternative scenarios can be compared in order to evaluate their impacts. Socio-economic developments replicate IEA, [60] assumptions and are consistent with the SSP2 scenario widely used by the IPCC. For the EU, socio-economic assumptions are based on the Ageing Report of the European Commission [61]. The Reference scenario assumes that already adopted climate policies and pledges, including the Nationally Determined Contributions (NDCs) are implemented by 2030. After 2030, no additional emission reduction effort is assumed for non-EU countries implying that the carbon prices resulting from NDCs in 2030 are kept constant until 2050. The costs of power generation and other energy technologies are calibrated to [62], while technology progress is included for low-carbon technologies. As GEM-E3-FIT results crucially depend on the adopted carbon revenue recycling scheme, in the current study we assume that ETS carbon revenues are recycled through the public budget. To ensure consistency with the overall INNOPATHS research, the scenario is fully consistent with the Reference scenario described in detail in INNOPATHS Deliverable D4.1.

4.3.2.2 *Ambitious climate policy scenario to well-below 2ºC*

A scenario consistent with the 2ºC Paris Agreement goal is examined. In line with the INNOPATHS Deliverable D4.1 and previous research, the global cumulative CO_2 budget up to 2050 is used as proxy for the temperature target; in line with the IPCC 5th Assessment Report, the CO_2 budget is constrained to 1000 GtCO2 over 2010-2050. A universal carbon price is implemented across regions from 2020 onwards to reach the cumulative CO_2 budget ensuring that the temperature increase relative to pre-industrial levels will stay well-below 2ºC. The carbon price is increased up to the level where the global carbon budget target is met. As the stringency of the mitigation effort increases over time, the global carbon tax grows from 80$/tnCO2 in 2030 (in line with [60]) to about 350$/tnCO2 in 2050. The contribution of each region in the global mitigation effort is determined by equal marginal abatement costs and uniform global pricing across countries and sectors. Therefore, the 2ºC scenario represents the solution that meets the global carbon budget constraint with the minimum costs through equalisation of marginal abatement costs in regions and sectors.

4.3.2.3 *Alternative climate policy scenarios*

In order to conduct a comprehensive analysis of the distributional impacts of EU climate policies on low-income households, the GEM-E3-FIT model is used to estimate

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

the impacts of asymmetric climate policies in different regions. The table below presents the main policy assumptions for the scenarios considered.

The "EUGD-Alone" scenario assumes that the European Union unilaterally adopts ambitious climate policies to achieve the EU Green Deal targets of GHG emission reduction of 55% in 2030 relative to 1990 and prepare the ground for the transition to climate neutrality by mid-century. As the EU Green Deal does not separately set a target for ETS and non-ETS, an EU-wide uniform carbon price is used in the model from 2025 onwards. The policy mix adopted in order to drive the EU energy system decarbonisation includes various instruments, e.g. strengthened EU ETS, subsidies to perform insulation in buildings, accelerated expansion of renewable energy, ambitious technology standards, subsidies for low-carbon Research and Innovation, increased electrification of energy and mobility services, mostly through the uptake of electric vehicles and heat pumps and deployment of disruptive mitigation options required for the transition to neutrality (e.g. Carbon Capture Use and Storage, green hydrogen, production of clean synthetic fuels). In contrast, non-EU countries follow the Reference policy setting and thus they meet their NDCs in 2030 and do not increase their policy ambition beyond 2030.

It should be noted that the general equilibrium modelling integrates results from the low-carbon transition pathways, as developed in INNOPATHS WP3. In particular, energy system projections from the "Weak" and "1p5" scenarios are integrated into the GEM-E3-FIT modelling for the "REF" and "EUGD-Alone" scenarios respectively.

Table 8: Scenario description

	Scenario Description	EU Climate target	Non-EU climate targets
REF	Reference scenario	Meets the EU NDC in 2030, no additional efforts after 2030	All countries meet their NDCs in 2030, policy ambition does not increase beyond 2030
2DEG	Decarbonisation to 2°C with all options available	All countries adopt ambitious climate policies/universal carbon pricing to meet the 2°C temperature target	
EUGD_Alone	EU meets the EU Green Deal Targets by 2030 and 2050	EU achieves 55/90% reduction in 2030/ 2050 from 1990	All countries meet their NDCs in 2030, policy ambition does not increase beyond 2030

4.4 Distributional implications of ambitious climate policies

The section explores the socio-economic and distributional impacts of ambitious EU climate policies towards climate neutrality by mid-century, focusing on income inequality and energy poverty for low-income classes by 2030 and 2050.

4.4.1 The Reference scenario

The global economic outlook implemented in GEM-E3-FIT builds on the socio-economic projections of the EC, Ageing Report 2018, IMF and SSP2 projections for non-EU countries. It should be noted that the current study does not take COVID-19 impacts into account, which will change the short and medium-term economic outlook. In the Reference scenario, the global economy is projected to grow 2.7% annually until 2050, while the average annual growth for the EU-28 is 1.5% largely driven by its ageing population. Among major economies, China and India will register high GDP growth

"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"

rates of 3.8% and 6.1% annually over 2015-2050 and increase their share in global GDP from 20% in 2020 to 30% in 2050. In the model-based economic outlook, countries adopt a sustainable growth path where excessive surpluses or deficits are reduced. The global economy is assumed to become increasingly interconnected over the coming decades, with the trade-to-GDP ratio increasing, which is induced by the gradual tariff reduction, diminished transportation costs and digitalisation of the economy. In terms of sectoral production, global economy will become more service oriented and go through a process of dematerialisation (less use of primary materials, increased resource efficiency, reduced share of energy-intensive manufacturing). Services will dominate global GDP (more than 60%), whereas the share of the primary sector continues to decline following historical trends and increased standards of living. Population projections are derived from the UN World Population prospects, 2019 (for non-EU countries) and the Ageing report (for EU countries) with the global population reaching 9.7 billion by 2050, increasing with an 1.1% average annual growth over 2020-2050.

In the Reference scenario, all countries implement their NDC targets until 2030 and do not intensify their ambition after 2030. In this context, economic activity and GHG emissions are expected to gradually decouple over 2020-2050. The GHG intensity declines in all countries (by about 2% annually over 2020-2050), as GDP grows at a faster pace than GHG emissions due to the deployment of renewable energy, improving energy efficiency, fuel switching and stricter environmental regulations. The carbon intensity of GDP constantly declines over 2020-2050 resulting in more efficient use of energy resources, through the uptake of energy efficient equipment, low-carbon technologies and energy carriers (e.g. electrification instead of oil products and coal).

As the aim of the study is to assess the distributional impacts of climate policies, the disaggregated household-related projections by income decile should be constructed ensuring consistency with the Reference national-level GEM-E3-FIT outputs. Projections for income deciles are developed for income level and source, occupation, consumption patterns and savings, largely based on developing simple rules (based on empirically estimated relationships) to disaggregate household energy demand by income decile.

The recent evolution of income distribution among deciles shows limited changes between 2013 and 2018 with small variations in the income shares of the bottom and top income quintiles. In particular, the share of income for the lowest decile in the EU fell from 2.9% to 2.8%, while the share of top earners slightly increased from 23.8% to 24.1% [33]; limited changes are observed for all EU Member States (with maximum changes in the order of 0.6%-0.7%). [36]) confirms that Europe has and will continue to have low income inequality rate, which depends on social policies regarding education, training and taxation to redistribute resources to the lower deciles. Eurostat data illustrate large differences in earnings within countries and per occupation type. The EU28 mean monthly earnings for professionals have increased by 300 Euros overs 2006-2014, while the elementary occupations have seen a decrease in earnings in the same period (minus 99 euro) [33]. Therefore, the income distribution across deciles will be endogenously determined by GEM-E3-FIT through wage evolution of different occupation types and their respective distribution across deciles and depending on sectoral evolution and labour-intensity of the economy.

Empirical evidence suggests that there is low occupational mobility across Europe. The link of occupational to wage mobility was studied in [63] using Eurostat's worker-level micro data and found that 3% of European workers change their occupation per year, but the size of occupational mobility differs strongly by country (e.g. 7.4% in

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Sweden versus 0.5% in Romania), largely influenced by national labour institutions. In addition, occupational mobility is associated with earnings mobility and occupation changes [64]. The Annual Report on Intra-EU Labour Mobility assessed the changes in occupation groups within and between European countries and showed that occupation type of professionals increased within countries, whereas elementary occupations mainly increased between European countries [64].Therefore, in the projection period, a constant distribution of occupation types by decile is assumed, so that the % shares of an occupation in a respective decile by 2050 follow the base-year data. This assumption allows for changes in income shares by occupation per decile, but assumes that the ranking between earnings of different occupation types remains rather unchanged.

According to [8], saving amounts are highly concentrated in the top of the income distribution and saving rates increase with income. In most countries, the poorest households have a zero or even negative saving, as they consume more than their income. Over time, saving rates as a percentage of household disposable income do not vary largely [33], and can be assumed as constant in the projections. Lower income deciles spend a higher share of their income on goods and services, implying that they have lower saving rates than high income ones. Saving rates by decile are assumed to remain unchanged in the Reference scenario over time by 2050.

The disaggregation of GEM-E3-FIT model output into income deciles requires a series of additional assumptions, including:

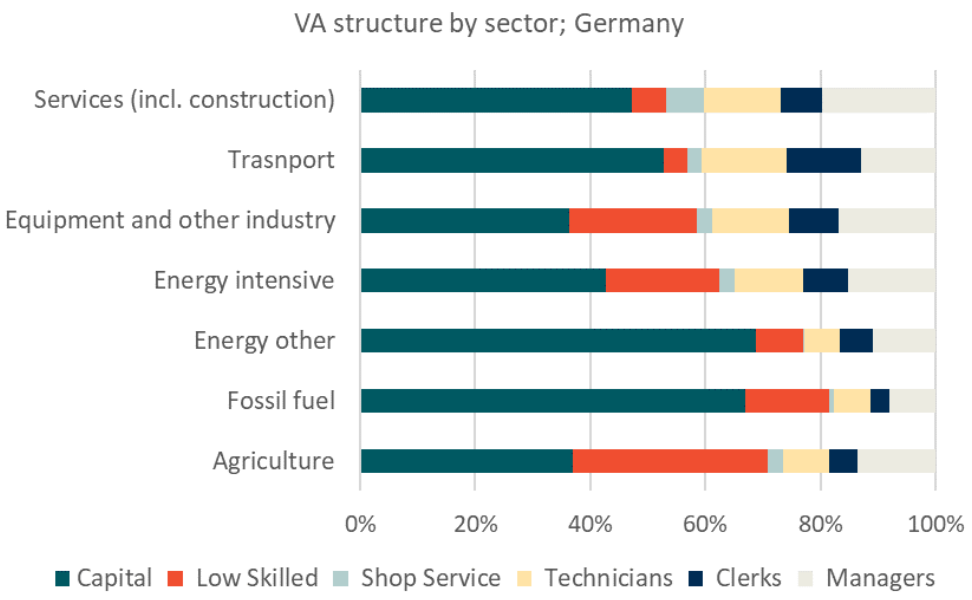
- Within decile, the income distribution is assumed constant over time
- The equivalized household size is assumed constant over time
- Consumption patterns and tax rates by decile are assumed constant over time
- Distribution of personal and household benefits and allowances from government by deciles is assumed constant over time

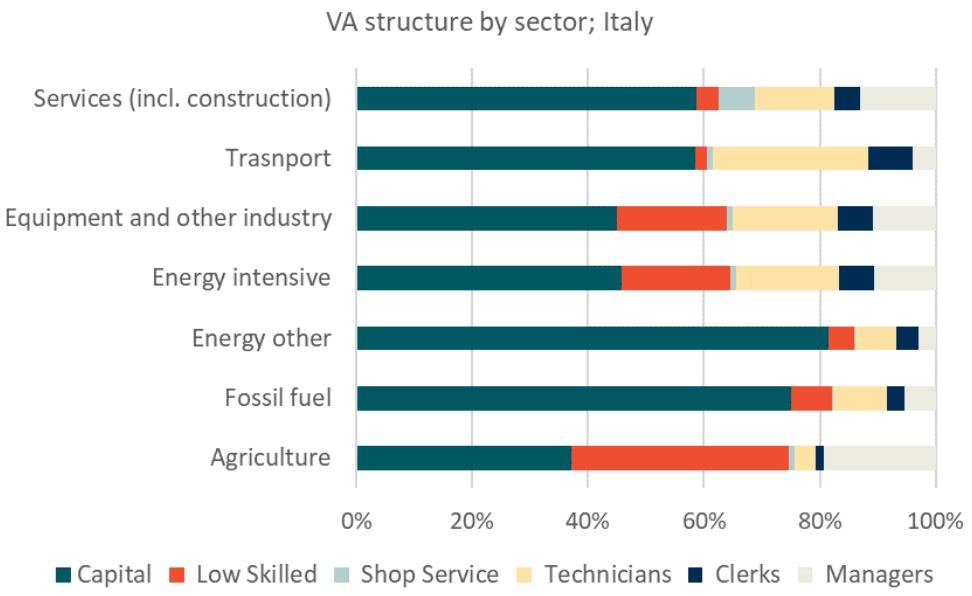
Technical progress, ageing population, capital accumulation, changes in consumer behavior, consumption patterns and industrial competitiveness and various policies shape the structure of the socio-economic developments in EU countries. This section presents how income distribution among and within EU countries changes over time in Reference scenario, which provides the benchmark against which the distributional impacts of climate policies can be evaluated. The analysis is based on the linkage of GEM-E3-FIT model with a satellite household module that identifies households by income deciles and attributes to each decile specific labour skills, income, consumption and saving patterns.

Changes in income distribution among and within EU MSs over time are largely driven by: the overall GDP growth, labour supply and demand by skill, technical progress, sectoral growth, wage differentials across skills and the distribution of skills, capital earnings and transfers across income deciles. The demand for different labour skills and capital is defined by the production structure of each sector. The composition of value added differs significantly across sectors and countries indicating that a specific policy can have different distributional and socio-economic effects across countries (Figure 7).

Figure 7: Structure of sectoral value added in Germany and Italy, source GEM-E3-FIT

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*





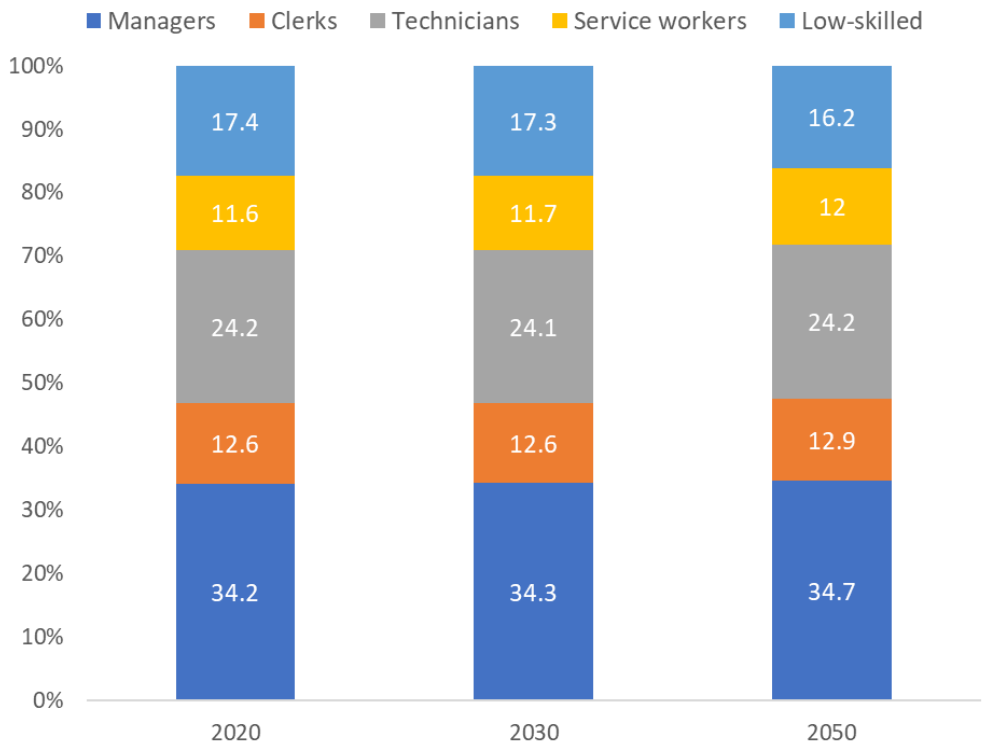
Scientific literature [65, 66] illustrates that income inequality is primarily influenced by inequality in labour skills and wages. As the growth of the European economy is driven mostly by the services sector, a changing mix of occupations and skills is required by the market, affecting the income of different households. Each household, depending on its labour skills features and the wage differential across skills, receives a share of the total wage income of the economy, based on the distribution of labour income by decile for each skill. Each household group receives income from different skill types. The wage income from low skilled occupations and service workers is more equally spread across different deciles, while income from high skilled occupations (e.g. managers, technicians) and dividends is mostly directed to higher income deciles. In contrast, low-income households receive most of social benefits and other allowances. A similar distribution pattern is registered in all EU countries with small variations. Different policy scenario assumptions can result in different inequality levels, as income

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

distribution is affected by changes in sectoral mix, skill wages, capital earnings, government benefits and taxation.

The development of the EU economy in the Reference scenario involves a gradual transition towards a more service-oriented, technology-rich economy, resulting in slight redirection of labour demand towards higher skills. In particular, over 2020-2050 there is a slight decline in the value-added share (Figure 8) generated by low skilled occupations (e.g. agricultural jobs) and an increase in share of higher skilled jobs (e.g. managers).

Figure 8: Composition of EU labour value added by skill in Reference scenario



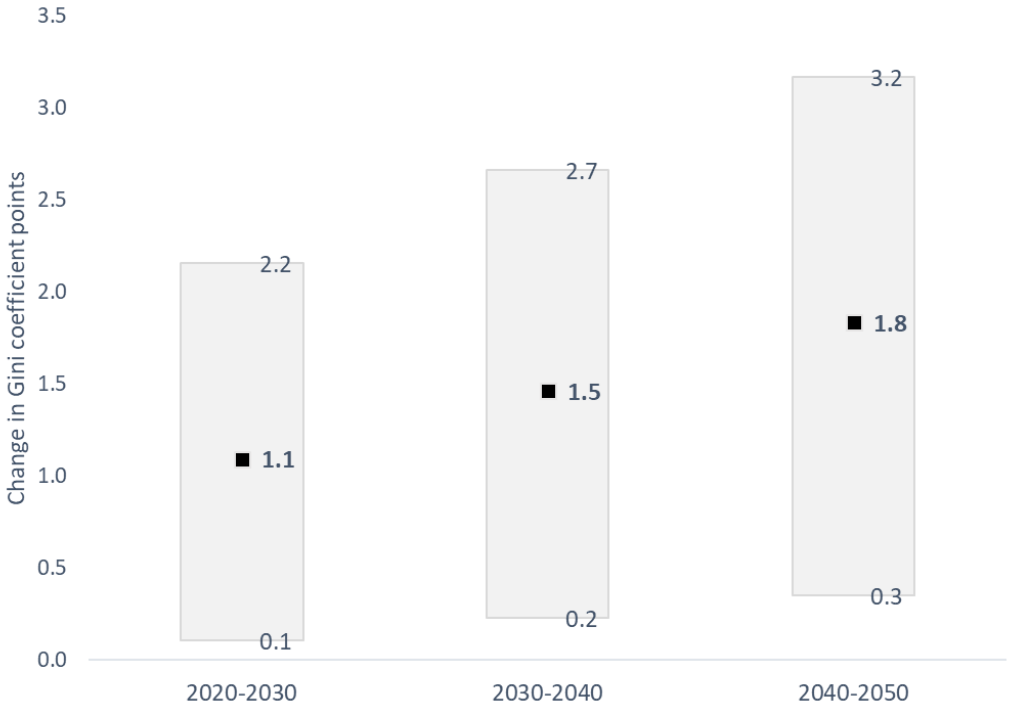
The change in occupations and labour skills has direct impacts on the distribution of income across income groups. As demand for high skills grows, a higher share of the total wages would be directed towards higher deciles. Low-income groups receive income mainly from low-skill occupations, and thus their income is negatively affected. The increasing capital-intensity of the European economy in the Reference scenario results in higher shares of income from dividends to the detriment of government benefits for all income groups. However, low-income deciles are dependent on government benefits and allowances and are thus negatively affected, while higher deciles receive income mostly from labour and to a lesser degree from capital endowments.

The transition towards high-skill and capital-intensive European economy results in increasing income inequality within EU countries across time in the Reference scenario as indicated by the Gini coefficient and the S80/S20 index for each Member State (Figures below). The overall income inequality in the EU depends on inequality both across and within Member States. The inequality indicators strongly depend on the assumption for constant distribution of occupations across deciles, which faces limitations as it does not consider the impacts of potential labour supply adjustments induced by the transition to high skills, which may change skill distributions across the deciles.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

The Reference scenario dynamics result in limited increase in the Gini coefficient from 2020 levels by 1.1 and 1.8 percentage points (pp) in 2030 and 2050 respectively, showing that inequality increases over the period 2020-2050. The increase ranges between [0.1-2.2] pp in 2030 and [0.3-3.2] pp in 2050 across EU Member States (Figure 9). The changes over time in the Reference scenario are limited and thus there is small variation in the relative inequality in EU countries, e.g. Belgium, Slovakia, Finland and Slovenia remain the most equal countries by 2050.

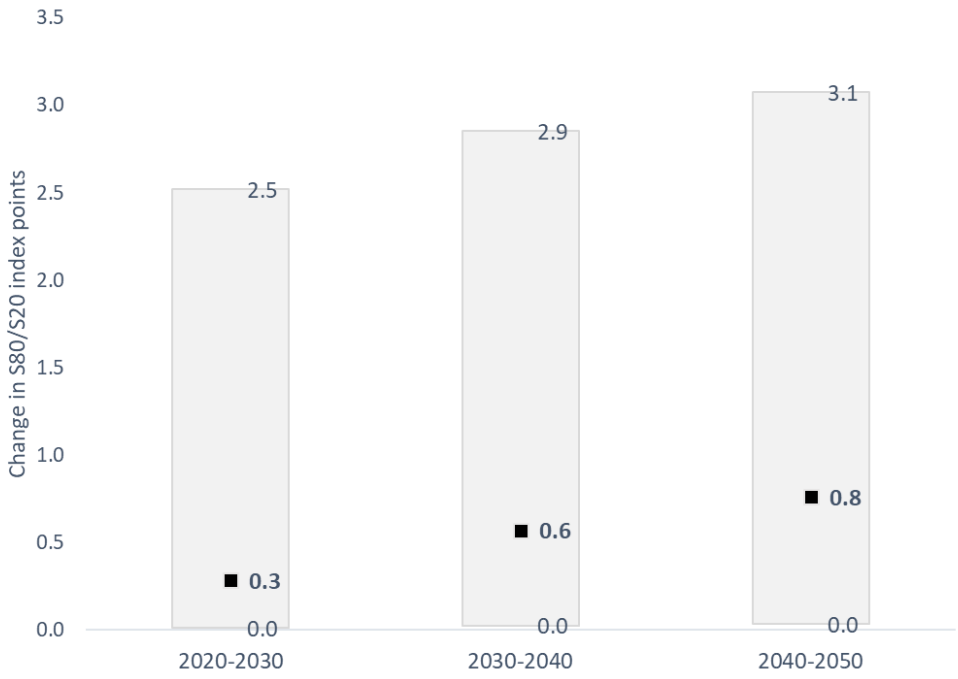
Figure 9: Change of the Gini coefficient over time in the Reference scenario (average, minimum and maximum values across EU countries); source: GEM-E3-FIT.



The S80/S20 indicator also shows limited increase over time in the Reference case by 0.3 and 0.8 percentage points (pp) from 2020 levels in 2030 and 2050 respectively. The increase ranges between [0.0-2.5] pp in 2030 and [0.0-3.1] pp in 2050 across EU Member States (Figure 10). The changes over time in the Reference scenario are limited and thus there is small variation in the relative inequality in EU countries over 2020-2050.

Figure 10: Change of the S80/S20 indicator over time in the Reference scenario (average, minimum and maximum values across EU countries); source: GEM-E3-FIT.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*



4.4.2 Distributional impacts of EU ambitious climate policies

The implementation of ambitious climate policies towards the EU Green Deal and the long-term climate neutrality target would have large-scale impacts on energy system transformation, triggered by the uptake of renewable energy, the acceleration of energy efficiency improvements, the massive electrification of energy and mobility services and the deployment of new disruptive mitigation options, including CCS and green hydrogen. The detailed PRIMES model results for energy system restructuring in "1p5" scenarios (developed in INNOPATHS WP3) are used as an input to GEM-E3-FIT, which is then used to estimate the socio-economic and distributional impacts across and within EU Member States over 2020-2050. Two main scenarios are explored which mostly differ on the assumptions about climate action in EU and non-EU regions. The 2DEG scenario[18] describes a world where all regions implement ambitious climate policies based on common carbon pricing across regions and sectors in order to stay below the 2ºC Paris Agreement goal, while in the EUGD_Alone scenario non-EU regions follow the Reference scenario assumptions, based on the implementation of NDCs by 2030 and the continuation of this moderate ambition until 2050.

4.4.2.1 *Macro-economic effects*

The imposition of high carbon pricing in the 2DEG scenario drives energy system restructuring towards a more capital-intensive structure, with increased investment to renewable energy, electric cars and energy efficiency projects. The low-carbon transition would lead to increased capital expenditures and lower energy purchasing costs in the

[18] The current study focuses on the economic implications of ambitious climate policies and does not consider the avoided damages and potential economy, health and air quality benefits from mitigating climate change.

"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"

long term. As GEM-E3-FIT assumes optimal use of available capital resources in the Reference scenario, the reallocation of investment towards low-carbon, energy efficient technologies and equipment in 2DEG leads to the so-called "crowding-out effect", as firms and households finance their clean energy investment by spending less on other commodities and investment purposes. High carbon prices increase the cost of energy services for firms and households and hence production costs throughout the economy and have a depressing effect on consumption and GDP, which is partly alleviated by increased investment in low-carbon technologies. Overall, the implementation of high carbon pricing in the 2DEG scenario result in a reduction of cumulative global GDP by 1.4% from Reference levels over 2020-2050[19] with differential impacts across countries, largely depending on their economic structure, their relative position in international trade (especially for fossil fuels and low-carbon technologies) and the level of mitigation effort. The GEM-E3-FIT results show a clear relation between emission reduction effort and GDP losses, while the latter are also influenced by the assumed costs and availability of CO_2 mitigation options and country-level specificities. In particular:

- Major fossil fuel exporters, like Russia and Middle East, would face large negative economic impacts due to their high carbon intensity per unit of GDP and the reduced revenues from fossil fuel exports
- Mitigation costs in large developing countries (China and India) are higher than in developed economies, as the imposition of universal carbon price leads to higher relative mitigation effort for developing countries
- The macro-economic impacts across developed economies are limited, on average less than 1% of their cumulative GDP, with very limited GDP losses in countries with low carbon intensities (EU, Japan) that already implement ambitious policies and in large low-carbon technology producers and exporters (Germany, Denmark)

High carbon pricing would have different implications by sector; in particular, sectors directly related to fossil fuel supply would face pronounced negative effects due to the shift towards low-carbon energy sources and more efficient use of energy. The global output of fossil fuel supply sectors would decline by about 40% from Reference levels in 2050. In contrast, the increased electrification of energy and mobility services drives increased demand for electricity required for the uptake of electric vehicles and heat pumps and the emergence of green hydrogen in the longer term. Therefore, the global output of the electricity sector increases by 5% from Reference levels in 2050 to provide the required electricity for mobility and heating services. The output of energy intensive industrial (EITE) sectors declines by about 2.5% from Reference scenario due to their carbon-intensive production structure, as energy costs (that increase due to high carbon pricing) represent a high percentage of their total production costs. The impacts of 2DEG scenario on the output of services are relatively limited, as the sector is characterized by low carbon intensity per unit of output. Energy efficiency improvements imply increased requirements for construction directed to building retrofits. Large positive impacts are projected for low-carbon manufacturing sectors, triggered by the increased demand of wind turbines, solar PV, electric vehicles, batteries, biofuels and green hydrogen.

[19] Economic costs emerging from high carbon pricing can be lower (or non-existent) if the benefits related to avoided climate impacts and air quality are explicitly quantified.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

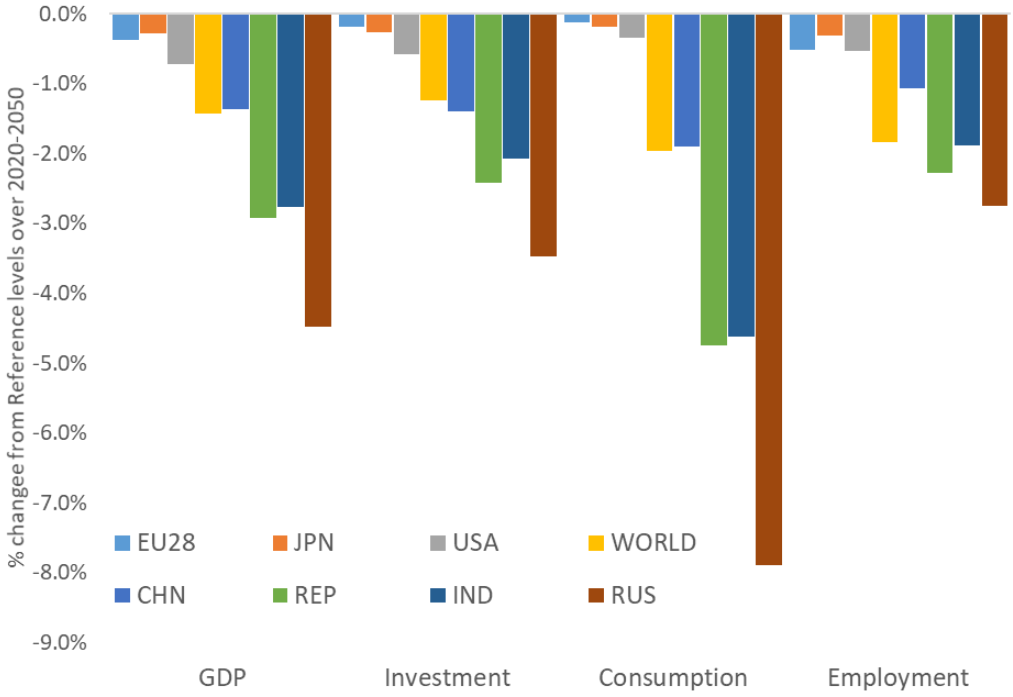


Figure 11: Macro-economic impacts across countries of the 2DEG scenario

4.4.2.2 ***Distributional implications through labour income***

The decarbonisation impacts on total employment are relatively limited and are mostly driven by declining economic activity counterbalanced by the transition to more labour-intensive technologies, e.g. renewable energy and energy efficiency [67]. The trade-off between jobs lost in some sectors and gains in employment in others leads to an overall limited impact on employment in most EU Member States. In contrast, GEM-E3-FIT results show that the low-carbon transition would lead to profound changes in employment at the sector level requiring extensive re-allocation of workforce and skill levels. The sectors most negatively impacted by the high carbon pricing are related to the production and transformation of fossil fuels, including coal mining, oil refineries, oil and gas extraction and coal power plants. Employment in the industrial sector is also negatively impacted, with energy intensive industries facing a high increase in their production costs due to carbon pricing. The impact on services is driven by the reduced GDP levels and affects millions of people, as services account for more than 65% of EU jobs. On the other hand, decarbonisation induces a high increase in jobs related to electricity and the manufacturing and development of low-carbon technologies. Overall, employment opportunities will not only be affected in sectors directly linked to energy transition, but also for workers at various levels of the supply chain or in sectors that observe a knock-on impact through multiplier effects (e.g. construction, agriculture). In addition, it is expected that larger impacts will be felt within, rather than between sectors.

The increased decarbonisation effort of the 2DEG and EU Green Deal scenarios results in slight deviations in the composition of EU value added with increased share of high-skill occupations in total income, while the share of low skilled decreases (Figure 12). This is triggered by the higher demand for high skilled labour required for the low-

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

carbon transitions and the wage differential across different occupations and skills (as e.g. an increase in the demand for managers results to a relatively higher increase in their respective share in labour income, as the former have higher wages). This skill transition is a feature of the energy system decarbonisation involving the replacement of labour-intensive and low-skill occupations, like coal mining, by skill-intensive processes related to the design, manufacturing, development and installation of clean energy technologies (e.g. wind, solar PV, batteries) and innovative low-carbon products. In the ambitious decarbonisation scenarios, the model-based analysis indicates employment losses in fossil fuel and certain energy intensive industries, while gains are registered in power supply and in the development of clean technology and equipment, which demand higher skill levels relative to fossil fuel supply sectors. Examples of occupations related to the low-carbon transition include software and manufacturing engineers, project designers, land development advisors and other high skilled professional or managerial positions.

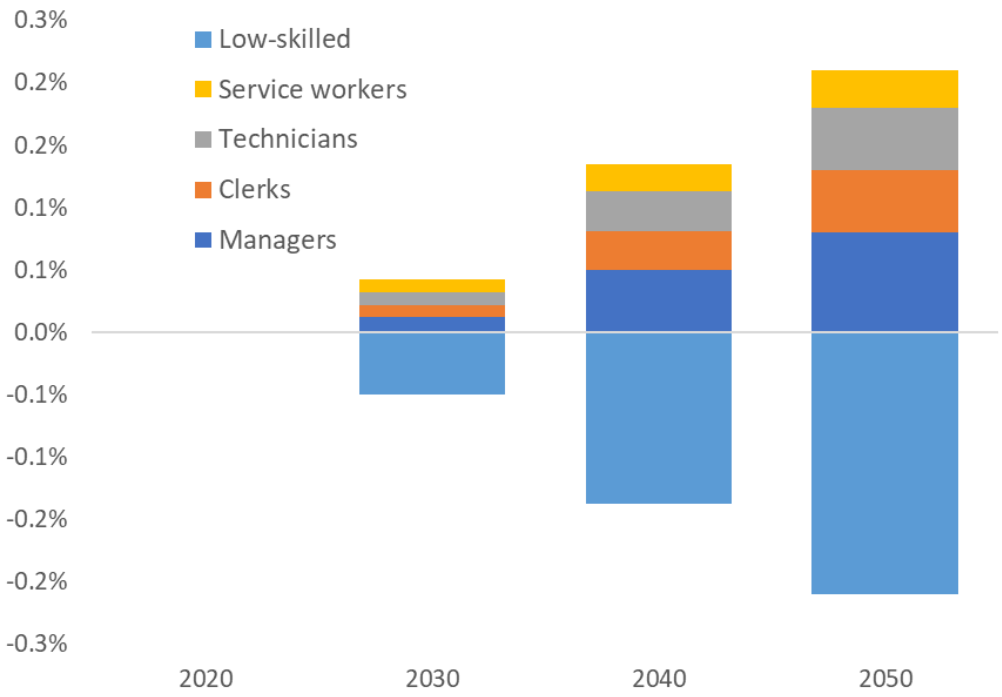


Figure 12: Changes in the composition of value added by skill in EU in 2DEG scenario compared to the Reference

The implementation of ambitious climate policies in the 2DEG scenario would lead to higher costs for energy services that have a subsequent depressing effect in the European economy as the EU GDP is projected to decline by 0.2% in 2030 and 1% in 2050 from Reference levels. Private consumption and employment are also negatively impacted with a reduction of about 1.2% from Reference in 2050. Higher unemployment levels put an increasing pressure on the average wage rate, which declines by 0.3% and 0.6% from Reference in 2030 and 2050 respectively. The labour income deteriorates by 0.6% in 2030 and 1.9% in 2050 in the 2DEG scenario relative to the Reference, which also depresses total household income. The largest impacts are felt in low-income deciles (Figure 13) thus slightly increasing income inequality across the EU, as the changes in the composition of value added by skill are limited.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

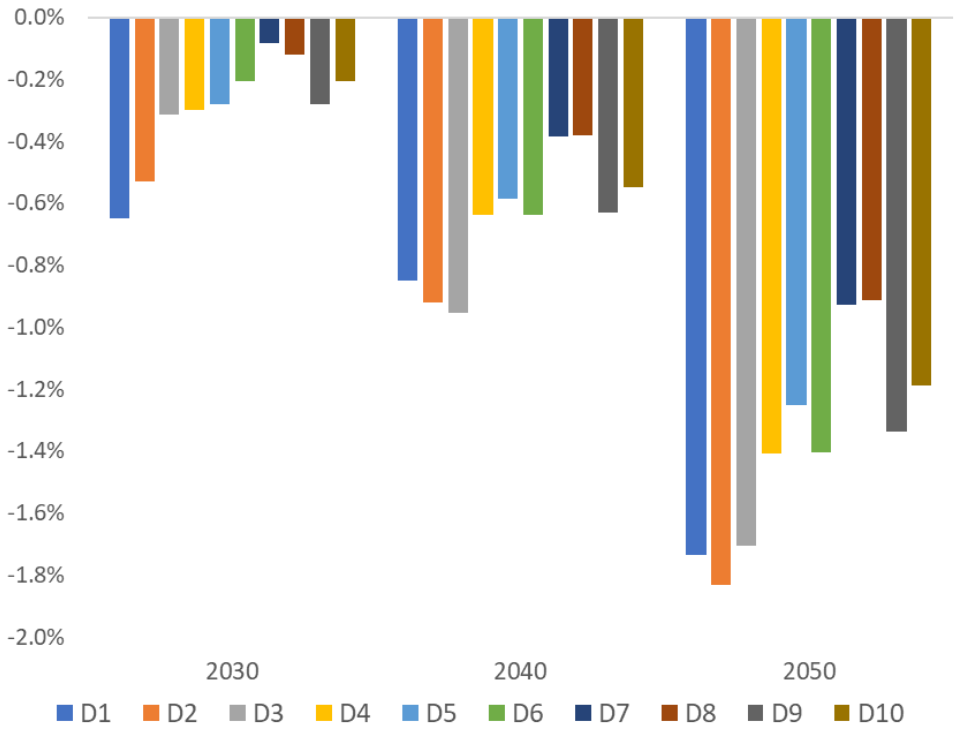


Figure 13: Change in total income per EU decile group in the 2DEG scenario relative to Reference over 2030-2050; source: GEM-E3-FIT.

The reduced income would have larger social impacts for low-income groups, increasing their vulnerability to energy and technology poverty. In order to alleviate such risks and ensure a more "just" and "equitable" low-carbon transition, we performed a model-based assessment assuming that ETS carbon revenues are redirected via lump-sum to households and via reduced social security contributions (2DEG_REC), instead of recycling them through the public budget. The distribution of lump-sum transfers to different income groups follows the distribution of social benefits and allowances in EU Member States. The additional ETS carbon revenues amount to about 0.5%-1.5% of EU GDP over 2030 and 2050 and thus the redirection of carbon revenues via lump-sum to households has an important effect on income and income inequality in the ambitious climate policy scenarios. The lump-sum increases the benefits and allowances distributed from the government, with most positive impacts for lower-income deciles, whose total incomes largely depend on benefits and allowances. Overall, the available income of the EU households increases from Reference levels over 2020-2050 (by more than 1% above Reference levels) but the increase is moderated in the longer-term by the macroeconomic effects of the low-carbon transition. As social benefits and allowances are a significant source of income for the lower income deciles, the highest increase is registered in these low-income decile groups in the entire period 2025-2050 (Figure 14), while the impacts are lower for high-income households and even turn negative in 2050, induced by the reduced overall economic activity (as in this scenario the EU GDP declines by about 1.3% relative to Reference in 2050).

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

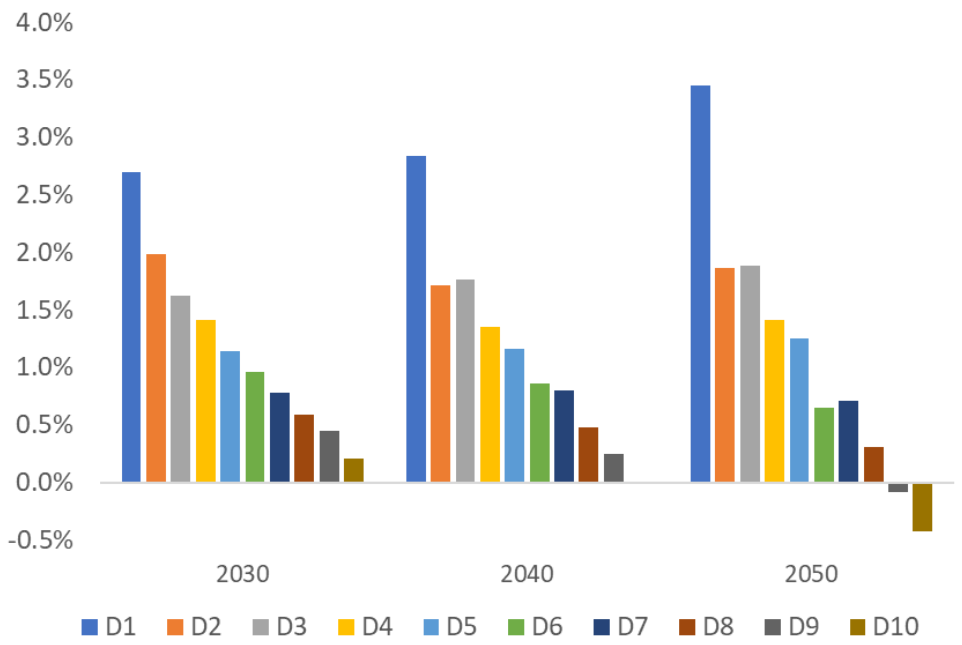


Figure 14: Change in total income per EU decile group in the 2DEG_REC scenario relative to Reference over 2030-2050; source: GEM-E3-FIT.

Overall, despite the slight move towards more high-skilled occupations, which are mostly found in higher income households, income inequality within Member States is improved illustrated by the reduction of Gini and S80/S20 indexes (Figure 15). The key driver to this positive distributional effect is the higher levels of income for the low decile groups in the 2DEG_REC scenario (Figure 14) due to the recycling of carbon revenues through lump-sum transfers that mostly benefit lower income households, as described above. Therefore, this policy tool has a counterbalancing effect to the impacts of skill transition and reduces income inequality within all EU Member States; in particular the Gini coefficient declines by 0.7pp and 1.3 pp on average across EU countries in 2030 and 2050 respectively relative to the Reference scenario, while the S80/S20 index also reduces considerably, pointing towards lower income equality. Overall, the recycling of ETS carbon revenues via lump-sum transfers to households and via reduced social security contributions has limited impacts to the overall activity growth, as key macroeconomic variables (GDP, consumption) remain very close to their 2DEG levels, but is beneficial for income inequality, which declines considerably.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Figure 15: Changes of the Gini coefficient (upper graph) and S80/S20 index in the 2DEG_REC scenario relative to Reference over 2030-2050; source: GEM-E3-FIT.

4.4.2.3 ***Distributional impacts through consumption expenditure***

The ambitious decarbonization scenarios entail a rapid and deep transformation of the energy supply and demand. In particular for households, the low-carbon transition

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

requires that consumers invest in renovation of buildings and purchase energy-efficient equipment and low-carbon technologies, e.g. electric cars, heat pumps, energy efficient appliances etc. As these options are capital-intensive, they require increased funding to meet higher upfront capital costs, which may be scarce and risky, posing additional challenges for low-income classes in EU countries. Although energy purchasing costs will be lower for households in the long term as a result of energy efficiency, the higher upfront capital expenditures required for the transition may create additional financial burden for low-income households, which cannot afford to purchase efficient appliances, houses and cars, thus increasing the threat of "technology" and "energy" poverty. The ability of households to meet their energy needs in a secure, reliable and affordable way is of primary importance when analyzing the social effects of the transformation. Energy affordability is affected by how income inequality changes due to the implementation of ambitious climate policies, as the amount of disposable income that is also available for energy-related expenditure is impacted.

The impacts of EU decarbonisation scenarios on energy expenditure by income class is measured with two indicators, namely "the share of energy expenditure for fuels and electricity in income" and "the share of energy expenditure for fuels/electricity and energy equipment in total income" by decile group. The indicators are quantified using GEM-E3-FIT model results for alternative policy scenarios, using data sources:

- Energy-related expenditure for fuels, electricity and energy equipment by EU Member State provided by the PRIMES model results for the INNOPATHS decarbonization scenarios
- HBS data to allocate national-level energy expenditure to household deciles
- Total income by income decile is provided by GEM-E3-FIT results for all EU Member States

The PRIMES energy system model provides detailed results for household energy purchasing expenses for each EU country, split by fuel type (gas, oil products, electricity, biomass, coal, hydrogen) and by energy use (e.g. private cars, space heating, electric appliances). In addition, the costs to purchase energy equipment, appliances and cars are also included in the PRIMES scenario projections and are used in the study.

The share of energy expenditure in income differs across Member States and income deciles, indicating the different levels of vulnerability to changes in energy prices across income groups. The share of energy expenditure to income (Indicator 1) is higher for lower-income deciles in all Member States; this indicator is estimated at 21% (average across EU countries) in 2020 for the lowest decile and ranges between 4%-50% among Member States, while for high-income households the indicator declines to about 3% of income in 2020. Eastern European countries are more vulnerable than Western ones, with lower income deciles registering very high shares of energy expenditures to their income; existing energy subsidies or other social policy measures directed to support the supply of energy services to low-income households are not considered. The figures below present the energy expenditure indicator 1 for EU Member States and income deciles in 2020. It is clear that households in Eastern low-income countries (e.g. Bulgaria, Estonia, Lithuania, Croatia, Latvia) face high challenges, as they register high shares of energy expenditure relative to their income. In contrast, households in the Netherlands, Sweden, France and Denmark spend a small share of their income for energy-related expenses.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Figure 16: Energy expenditure Indicator 1 by income decile for each Member State in 2020. Source: GEM-E3-FIT.

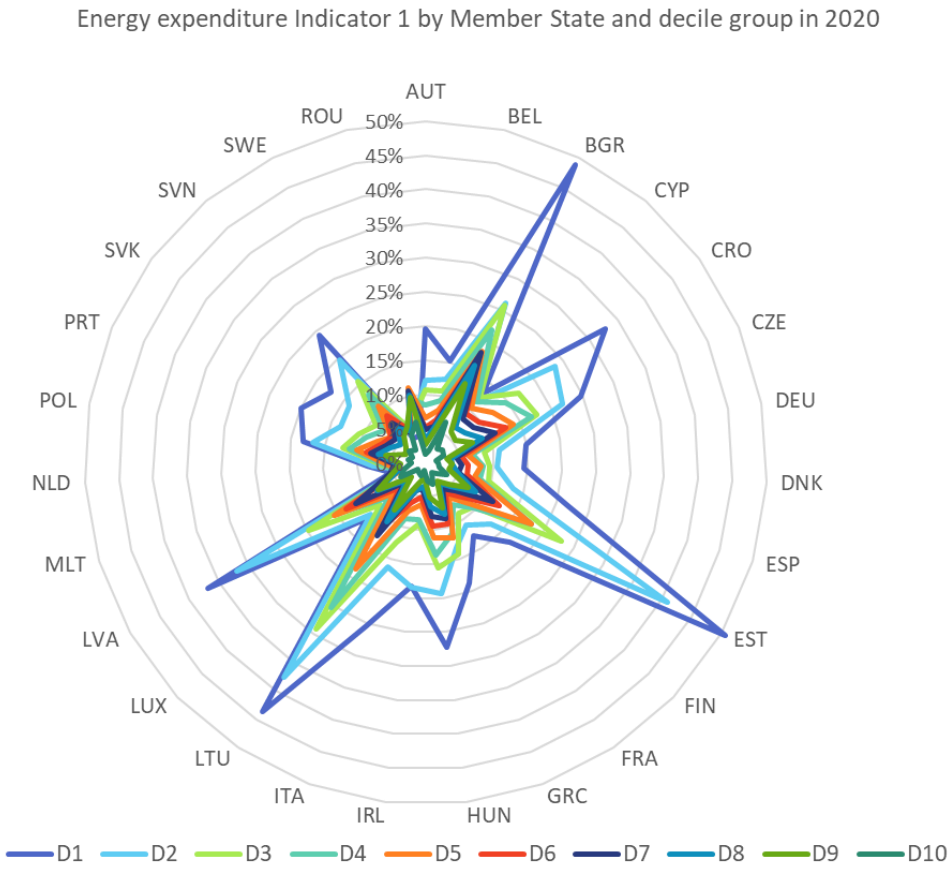
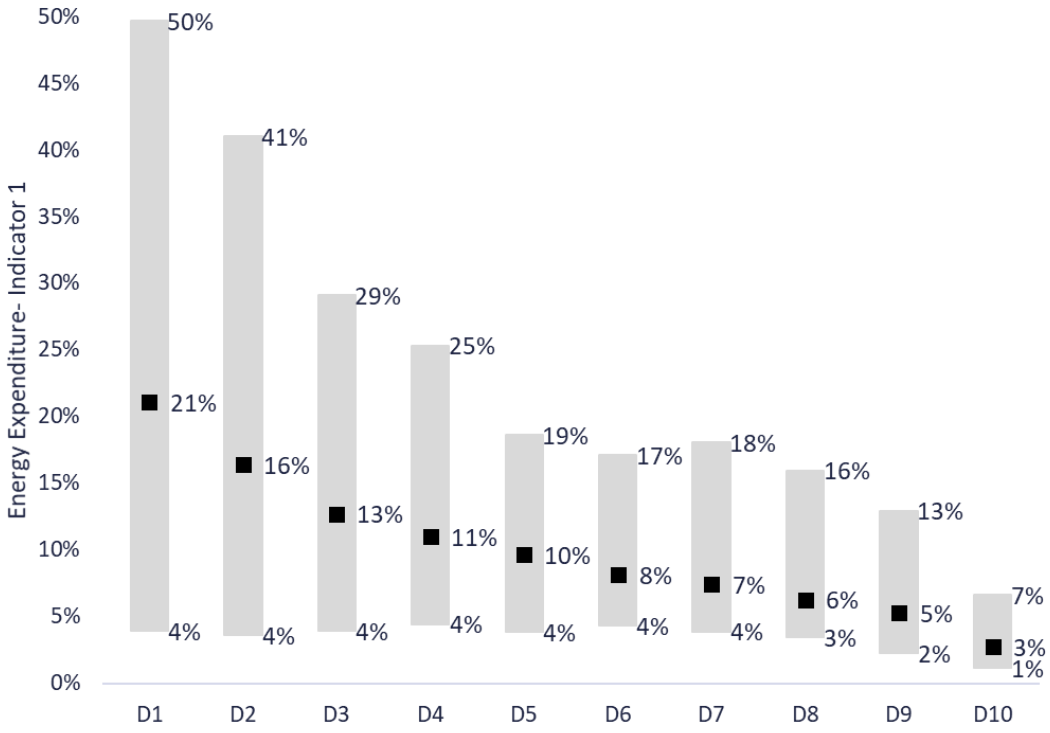


Figure 17 shows that the low-income households are more vulnerable to changes in energy prices, as they spend a higher share of their income for energy-related expenses. The situation is very different across EU Member States, as illustrated by the large ranges of uncertainty in all income deciles in Figure 17, implying that even medium-income households in specific low-income countries spend more than 15% of their income for energy-related expenditure (e.g. Bulgaria, Estonia and Lithuania).

Figure 17: Minimum, average and maximum values of the Energy expenditure Indicator 1 across Member States for each income decile in 2020

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*



When considering also the expenditure for energy-related equipment (including energy appliances, heating devices, cars and other transport equipment), the share of energy expenditure increases by an average of 5.9 p.p. across income deciles in 2020. Energy expenditure Indicator 2 registers relatively higher values for mid or high-income deciles compared to low-income deciles in certain member States (Figure below) as indicated by the HBS database, given that the households' expenditure on transport equipment and appliances are included in the indicator. The mid and high-income deciles commonly purchase more expensive energy-related equipment, highly energy efficient appliances and more luxurious cars relative to low-income groups. As a result, the average share of income spent of the highest decile increases from 3% to 9%, when the expenditure related to energy and transport equipment are included in the calculation.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

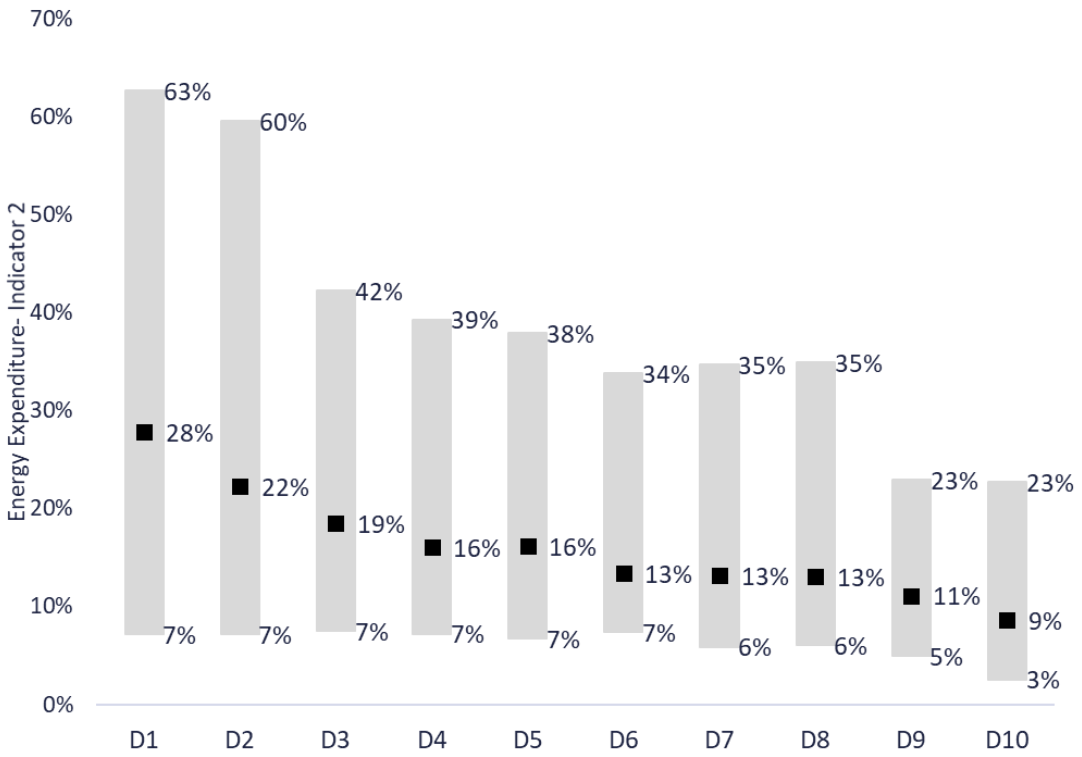


Figure 18: Energy expenditure Indicator 2 across EU countries by income decile in 2020

In the Reference scenario, the average share of energy expenditure to household income (Indicator 1) declines somewhat in the medium and long term across EU countries and income deciles, as household incomes increase faster than energy consumption and energy prices of households. This implies a slight reduction in the vulnerability of low-income households in energy price changes over time, as growth in energy consumption and prices of energy products in households (e.g. electricity, gas, refined oil products) grow at a slower pace relative to their income. The same trend is also evident when the expenditure for energy and transport equipment is added to the calculation (Indicator 2), with the average share of energy expenditure to income declining by about 1.5% across EU Member States and income groups.

Figure 19: Energy expenditure Indicator 1 across Member States for each income decile in the Reference scenario in 2050, Source: GEM-E3-FIT.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

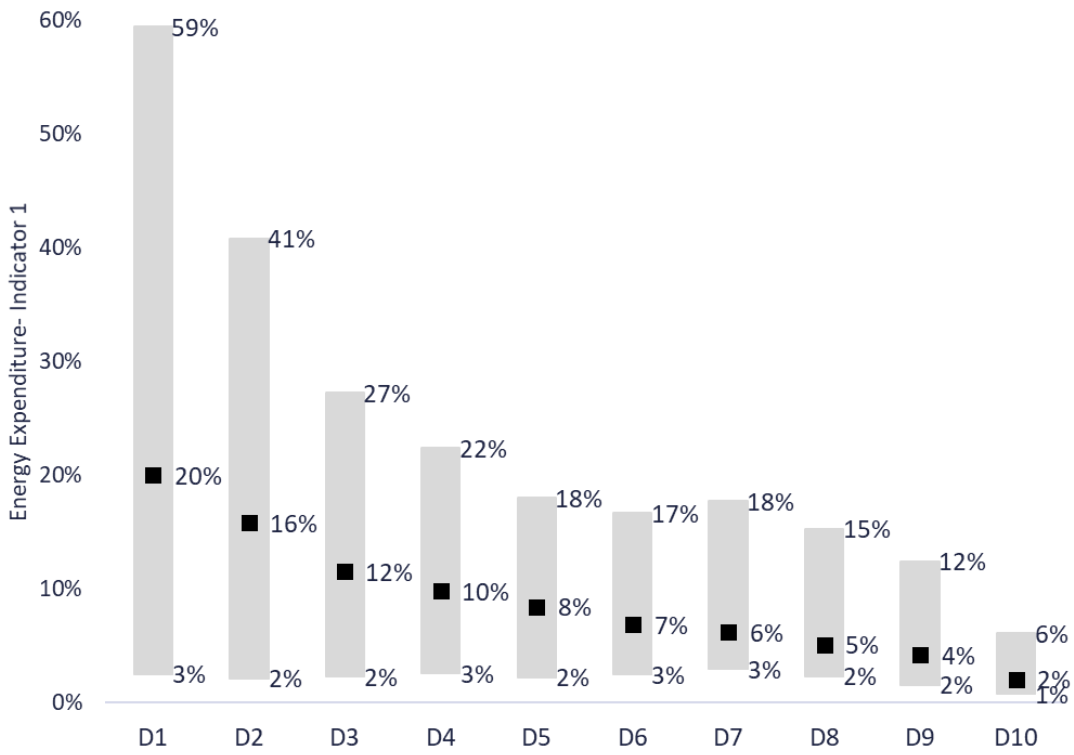
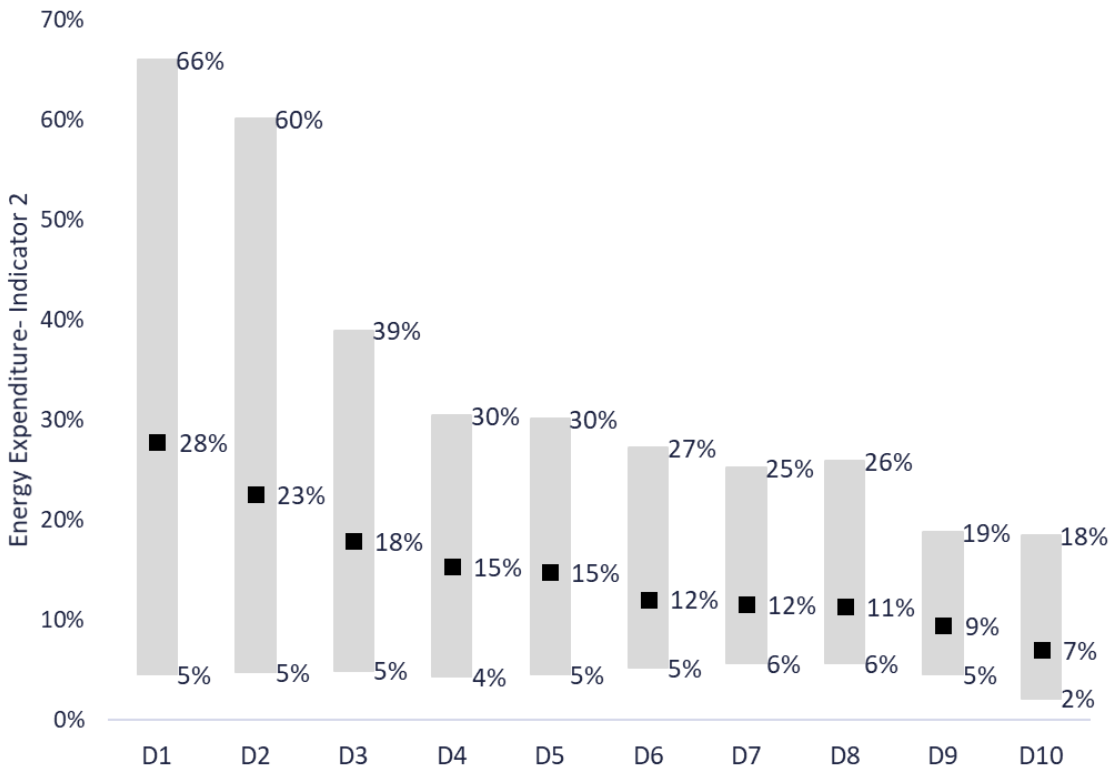


Figure 20: Energy expenditure Indicator 2 across Member States for each income decile in the Reference scenario in 2050, Source: GEM-E3-FIT



*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

The energy system transformation in ambitious decarbonization scenarios entails significant changes for household energy-related expenditure, along with the subsequent macroeconomic and distributional changes described in sections above. In particular, the implementation of ambitious climate policies, including high carbon pricing in the 2DEG scenario, would lead to increased energy expenditure across income deciles in most EU Member States, driven by increased prices of energy products. The EU-wide average Energy Expenditure Indicator 1 increases by about 1% pp from Reference levels in 2050, as the energy expenditure for fuels, transport services and electricity is higher compared to the Reference, while household income falls slightly. The highest increases are found in low-income classes, thus indicating additional challenges to purchase the required energy services for the most vulnerable groups leading to higher energy poverty risks. However, positive effects are registered for Member States with high values for Energy Indicator 1 in the Reference scenario, e.g. Bulgaria, Latvia, thus improving their energy affordability. The magnitude of changes varies widely across Member States with lower impacts seen in the countries and deciles with the lowest values for Indicator 1 in the Reference scenario (Figure 21).

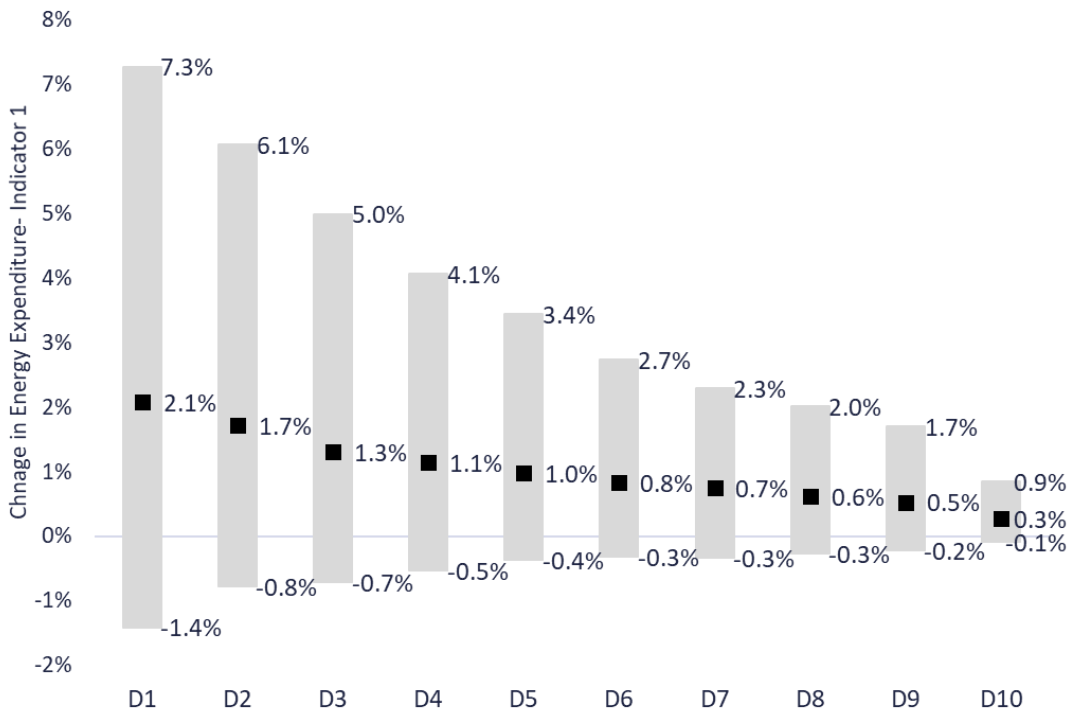


Figure 21: Changes in Energy expenditure Indicator 1 across Member States for each income decile in 2050 in the 2DEG scenario relative to Reference. Source: GEM-E3-FIT.

Once the expenditure for energy and transport equipment is considered (Energy expenditure Indicator 2), the average ratio in 2050 increases for all income groups (Figure 22) triggered by the increased prices of energy products and the increased expenditure of household to purchase more advanced energy-efficient equipment and low-emission cars, which commonly entail higher costs than conventional ones. This results in a higher increase in Indicator 2 relative to Indicator 1, as expenditure for energy and transport equipment grow significantly compared to the Reference scenario. The highest increase

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

is projected for low-income deciles, whose energy-related expenditure increase by about 2% of their income. The 2DEG scenario leads to lower energy-related expenditure in specific Member States that indicate high values of the Indicator 2 in the Reference (e.g. Bulgaria, Latvia), thus reducing their vulnerability in terms of energy affordability.

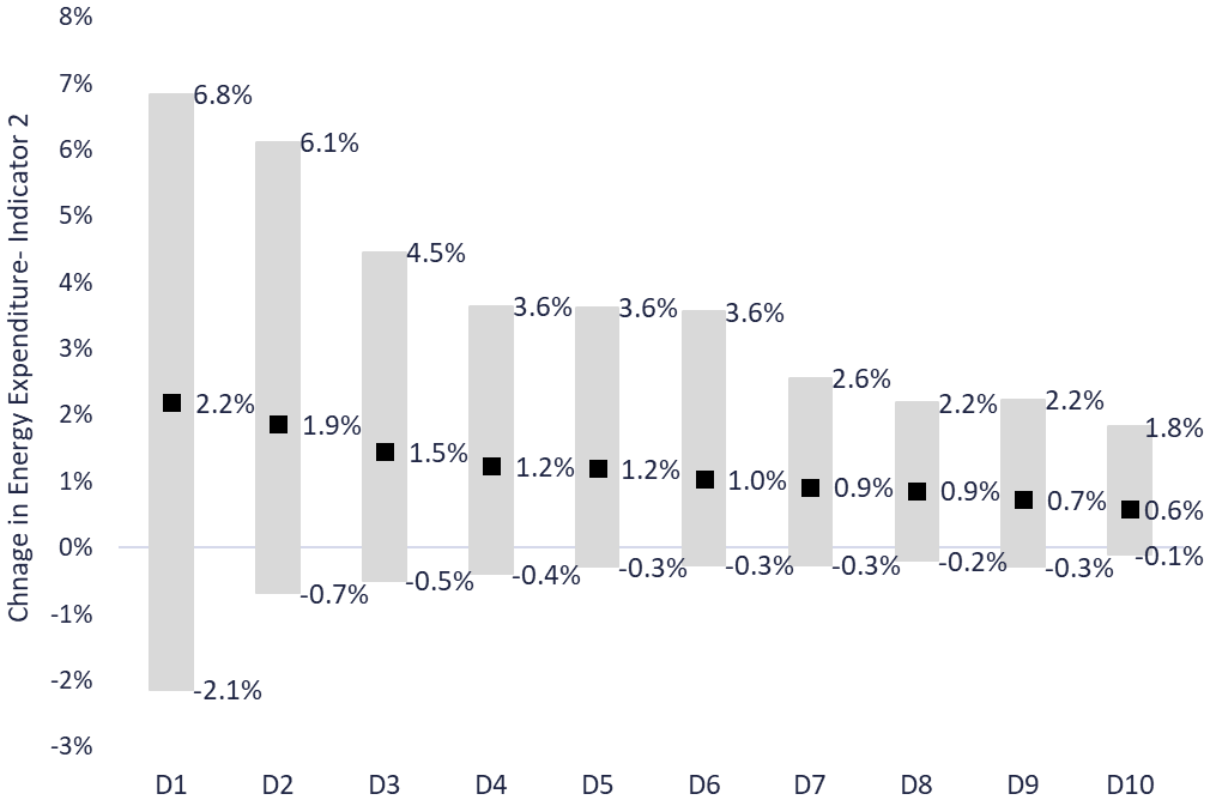


Figure 22: Changes in Energy expenditure Indicator 2 across Member States for each income decile in 2050 in the 2DEG scenario relative to Reference. Source: GEM-E3-FIT.

4.5 Policy Implications and Recommendations

The distributional impacts of decarbonisation in EU countries give rise to major policy implications and recommendations. Importantly, there is a large variety of policy measures to draw from to further address energy poverty and income inequality across Member States, since these are designed and implemented according to specific country situations [41]. This section below discusses the most important policy changes and drivers derived from our findings.

As **spatial disparities in labour markets** are large in many countries, mobility policies can facilitate movement to more productive areas, while supporting schemes for lagging regions can also be used [68]. For example, our results show that the low-carbon transition would result in a loss in low-skilled jobs, but can also increase higher quality jobs such as those of managers, clerks, and service workers (our results suggest that technician jobs stay roughly the same). This underscores the need for policy instruments that do more than just focus on economic growth or GDP and focus on the provision of the required labour skills to the market. Although the GDP, investment and employment

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

impacts of decarbonisation within EU may appear minimal, crowding-out occurs in GE-E3-FIT putting additional stresses in capital markets through a reallocation of investment as the model assumes optimal use of resources in the reference scenario. Labour market regulation to protect workers can be implemented to reduce income inequality and poverty [69]. Relevant policies may include: minimum wages, reduction of gender wage gap, strengthening of trade unions, job protection of temporary workers and improved labour market institutions so that they better match jobs with skills [26].

Given the negative impacts decarbonisation will have on income equity, various social protection measures are warranted. Our results underscore that the lowest income deciles are those that are most hardly affected by carbon pricing, as they have a higher share of low-skilled labour that experience job losses. Indeed, decarbonisation is found to have some regressive impacts across households induced both by a reduction in their incomes and the increase in energy-related expenditure. **Effective fiscal policies** can be used to redistribute income from top income classes to the bottom income classes [68]. Empirical evidence shows that transfer systems[20] decreased inequality in advanced economies by an average of one-third [70], with public pensions and family benefits accounting for the largest redistribution [71]. Moreover, education and health spending lower the Gini coefficient by 5.8% on average in five EU economies (Belgium, Germany, Greece, Italy, and UK) [71]. The distributive impacts of such transfers vary in size and progressivity, due to country differences in policies and institutions. The personal income tax tends to be progressive [26], while consumption taxes, value-added tax and excise duties are found to be regressive [70]. Although many studies explore the effectiveness of different fiscal policies on reducing inequality, there is no consensus, as some progressive taxes tend to increase tax avoidance behavior and are inefficient [72]. [73] argue that the property tax is effective in reducing income inequality, but its potential has not been used in many countries. [74] showed that capital income combined with a near-zero interest rate environment can significantly reduce wealth and income inequality. Finally, taxing inheritance is an effective way in addressing inequality as inheritance caused a large increase in the concentration of wealth in France [75]. For these reasons, the modelling outcomes show that if ETS revenues are redistributed via lump-sum to households and via reduced social security contributions, they can redirect resources to low-income households and effectively reduce income inequality. Especially the lump-sum has strong progressive effects as they increase disproportionately the income of low-income classes.

This is similar to "systems benefits charges" in the United States that redistribute electricity tariffs to poorer consumers or fuel poverty and weatherization programs that prioritize low-income homes in Europe. Without direct policy intervention, European decarbonisation truly rusks the risk that inequality across income deciles would increase with low-income households facing higher increases in their energy-related expenditure and larger income reductions than other groups. Many countries already have financial instruments for retrofit measures such as subsidies, tax incentives and low-interest loans. [76] found evidence that lower income households in European countries are less likely to adopt retrofit measures than higher income ones. The design and implementation of financial instruments (low interest loans, subsidies) targeting low-income households can effectively reduce energy poverty by enhancing the uptake of energy efficiency

[20] Public pensions, family benefits, health related benefits, unemployment benefits, social assistance benefits, housing benefits

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

technologies and retrofit measures. The efficiency of such schemes could be strengthened by setting quantifiable targets for the share of energy-efficiency measures to be implemented in low income households.

Additional **measures addressing energy poverty** can be targeted at supporting vulnerable consumers, through social security provision or energy poverty specific instruments [41]. [39] show that both social and energy policy mechanisms are needed. Implementing energy efficiency schemes in households can reduce energy poverty, through implementation of building insulation, efficient housing appliances, heating and cooling systems, and the uptake of renewable energy and energy storage systems. National energy efficiency schemes can facilitate increased rate and deepness of building insulation. Some programmes provide support to avoid inefficient and expensive space heating through the replacement of old boilers. The deployment of renewable energy and energy storage may allow energy poor households to produce and store energy for self-consumption in a decentralized way, while counteracting high energy prices [42].

Energy efficiency can be further improved through energy audits, while trained personnel can advise low-income households on how to reduce their energy consumption. Numerous energy audit programmes are implemented across EU countries often targeting to improve energy efficiency of low-income households. The impacts of the guidance offered in energy audits are difficult to assess. [77] studied the effectiveness of energy coaches for households in poverty in the Netherlands and found the average household can save up to 100 euros per year, which accounts for 5,2% of the energy expenditure of an average household in Netherlands [33]. The study showed that low-income households often gain the most from energy savings.

In some EU countries, **social support measures** are more specifically targeted for energy poverty, namely energy bill support, financial assistance to households to pay their energy bills. The financing for these programmes can be sourced from taxes on electricity and gas, as in the case of e.g. France's Energy Check. These programmes are designed to target vulnerable groups at risk of poverty, including low-income households and the elderly (e.g. in UK Winter Fuel Payments programme). Several EU countries implement additional consumer protections via social tariff schemes so as to mitigate the impacts from the frequent changes in energy prices. Social tariff schemes are a price regulation that reduces the tariff for certain households aiming to alleviate the burden of high energy costs for vulnerable consumers. In addition, disconnection protection instruments aim to prevent the disconnection of households from the electricity and/or gas networks. Most of these measures are implemented during winter months, where energy bills are higher especially in Northern EU countries (e.g. Finland, the Netherlands, France). [39] shows that measures focusing on vulnerable consumers, such as those in social housing or heating oil users, will be generally more effective at tackling energy poverty than non-targeted measures. This finding is especially apt given that our results suggest that Bulgaria, Estonia, and Lithuania are the countries set to lose the most via decarbonisation, as households in these countries register the highest energy expenditures as a share of their income. This underscores the need for social protection measures in these countries as well, to address emerging disparities from becoming entrenched.

4.6 Discussion and Conclusions

The increased ambition of climate policies would result in large-scale economic restructuring with potential regressive distributional impacts, disproportionately affecting

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

disadvantaged population groups. In particular, increased energy prices and the imposition of additional taxes on energy products may affect negatively the low-income households that face funding scarcity, by increasing the risk of energy and technology poverty. Distributional effects refer to how the gains and costs of a project or policy are distributed among its participants, which in terms of policy-making may refer to different regions, sectors, and households; the latter is the focus of the current study. Overall, environmental policies are usually associated with regressive distributional impacts in the literature, disproportionately affecting low-income households. Ignoring such possible distributional effects may, however, result in less effective policies and even increased inequalities due to the lack of measure to mitigate potential impacts. Well-designed strategies are required to achieve progressive outcomes by considering appropriate compensation schemes, either by increasing household income through lump-sum payments or reducing other taxes, or through the social security system.

In the current study, the state-of-the-art general equilibrium model GEM-E3-FIT is significantly expanded to represent ten income classes in all EU Member States, by differentiating their income sources, savings and consumption patterns. The enhanced model representation captures ten representative households, each one representing an income decile in EU Member States. The new methodological and modelling capabilities of GEM-E3-FIT are used to quantify the socio-economic and distributional impacts of the EU Green Deal policies and targets for 2030 and 2050. In particular, the climate policy impacts on the labour income by skill are analysed, showing a slight reduction in low-skilled labour demand combined with an increase in high-skilled jobs required for the clean energy transition. This raises negative distributional impacts through the labour market leading to higher income inequality levels. However, in case that ETS revenues are redistributed via lump-sum transfers to households and via reduced social security contribution, income inequality would significantly decline with high benefits for low-income households, as the distribution of lump-sum transfers follows the distribution of social benefits and allowances to different income groups. The imposition of ambitious energy and climate policies to achieve the EU Green Deal targets would increase the energy and transport-related expenditure in households. The largest impacts are projected for low-income households, raising the issues of energy poverty and energy affordability as these income classes already spend a large share of their income to purchase energy and transport services and equipment.

Overall, the model-based analysis shows that the transition to climate neutrality may increase modestly the inequality across income classes, with low-income households facing more negative effects than higher-income ones. However, using carbon revenues as lump-sum transfers to households and as reduced social security contributions has clear benefits increasing total employment, while reducing significantly the inequality across income classes in EU countries.

An important caveat of the analysis which can be improved in future research is the assumption that income distribution remains constant over time within deciles, which is rather simplistic. Of course, if additional data are provided and model running time is improved, the GEM-E3-FIT modelling framework can be further enhanced to represent income percentiles, thus improving its simulation properties, in particular for assessing policy impacts for the most vulnerable income groups.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

References

[1] Winkler, Harald, Höhne, N., Cunliffe, G. E., Kuramochi, T., April, A., & de Villafranca Casas, M. J. (2018). Countries start to explain how their climate contributions are fair: more rigour needed. International Environmental Agreements: Politics, Law and Economics, 18(Special Issue on Climate Justice and 1.5°C), 99–115. https://doi.org/10.1007/s10784-017-9381-x

[2] Mbeva, K. L., & Pauw, W. P. (2016). Self-Differentiation of Countries' Responsibilities Addressing Climate Change through Intended Nationally Determined Contributions. Bonn: Deutsches Institut für Entwicklungspolitik gGmbH.

[3] Mohai, Paul, David Pellow, and J. Timmons Roberts. 2009. Environmental Justice, Annual Review of Environment and Resources, Vol. 34:405-430, https://doi.org/10.1146/annurev-environ-082508-094348

[4] Jenkins, Kirsten. Setting energy justice apart from the crowd: Lessons from environmental and climate justice, Energy Research & Social Science, Volume 39, 2018, Pages 117-121

[5] Routledge, Paul et al., States of just transition: Realising climate justice through and against the state, Geoforum, Volume 88, January 2018, Pages 78-86

[6] Sovacool, B. K., & Dworkin, M. H. (2014). Global energy justice: Problems, principles, and practices. In Global Energy Justice: Problems, Principles, and Practices. https://doi.org/10.1017/CBO9781107323605

[7] Klinsky, S & Winkler, H 2018. Building equity in: strategies for integrating equity into modelling for a 1.5°C world. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 376 (2119) 20160461. http://rsta.royalsocietypublishing.org/content/376/2119/20160461.abstract

[8] OECD, The Distributional Effects of Environmental Policy, OECD, 2006.

[9] N. Ohlendorf, M. Jakob, J. C. Minx, C. Schröder, J. C. Steckel, Distributional Impacts of Climate Mitigation Policies: A Meta-Analysis, Deutsches Institut Für Wirtschaftsforschung (DIW), Berlin, 2018.

[10] G. Zachmann, G. Fredriksson, G. Claeys, The Distributional Effects of Climate Policies, Brüssel, 2018.

[11] OECD, The Distributional Aspects of Environmental Quality and Environmental Policies: Opportunities for Individuals and Households, 2019.
[12] M. Zimmermann, S. Pye, Energy Policy 2018, 123, 594–601.

[13] OECD, The Distributional Aspects of Environmental Quality and Environmental Policies: Opportunities for Individuals and Households, 2019.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

[14] GBD 2017 Risk Factor Collaborators, The Lancet 2018, 392, 1923–1994

[15] EC (2017), European Semester Thematic Factsheet: Addressing Inequalities. (Online) EC. Available at: https://ec.europa.eu/info/sites/info/files/file_import/european-semester_thematic-factsheet_addressing-inequalities_en_0.pdf

[16] Carvalho, L., & Rezai, A. (2015). Personal income inequality and aggregate demand. Cambridge Journal of Economics, 40(2), 491-505.

[17] Stiglitz, J. E. (2012). The price of inequality: How today's divided society endangers our future. WW Norton & Company.

[18] EC (2018), The EU-wide income distribution: inequality levels and decompositions

[19] UN (2015), Inequality measurement: Development issue no 2. In Development Strategy and Policy Analysis Unit, Development Policy and Analysis Division Department of Economic and Social Affairs. (Online)

[20] IMF (2015), Causes and Consequences of Income Inequality: A Global Perspective. (Online) IMF. Available at https://www.imf.org/external/pubs/ft/sdn/2015/sdn1513.pdf

[21] OECD (2017). Understanding the Social Divide in Europe. (online) OECD. Available at: https://www.oecd.org/els/soc/cope-divide-europe-2017-background-report.pdf.

[22] OECD (2011). “Growing Income Inequality in OECD Countries: What drives it and how can Policy tackle it.” (Online Available

[23] Furceri, D., & Loungani, P. (2013). Who let the gini out? Finance & Development, 50(4), 25-27.

[24] Tridico, P. (2017). “The determinants of income inequality in OECD countries”. Published by Oxford University Press on behalf of the Cambridge Political Economy Society

[25] Stiglitz, J. E., & Greenwald, B. C. (2014). Creating a learning society: A new approach to growth, development, and social progress. Columbia University Press.

[26] OECD (2012). "Reducing income inequality while boosting economic growth: Can it be done?", in Economic Policy Reforms 2012: Going for Growth, (Online) OECD Publishing, Paris.

[27] Bubbico, L. and Freytag, L. (2018). Inequality in Europe. (online) European Investment Bank (EIB). Available at: http://www.eib.org/attachments/efs/econ_inequality_in_europe_en.pdf.

*“This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Grant Agreement No **730403**“*

[28] Piketty, T. (2014). Capital in the Twenty -First Century. Cambridge, MA: Harvard University Press

[29] Cagetti, M., & De Nardi, M. (2008). Wealth inequality: Data and models. Macroeconomic Dynamics, 12(S2), 285-313.

[30] Fuller, G. W., Johnston, A., & Regan, A. (2019). Housing prices and wealth inequality in Western Europe. West European Politics, 1-24.

[31] Haughton, J., & Khandker, S. (2009). Inequality measures. Handbook on poverty and inequality. Washington, DC: The World Bank, 101Á20.

[32] De Maio, F. G. (2007), Income inequality measures. Journal of Epidemiology & Community Health, 61(10), 849-852.

[33] Eurostat (2019c). Eurostat Statistic Explained: People at Risk of Poverty or Social Exclusion. Edition 2018. (Online) Retrieved from: https://ec.europa.eu/eurostat/

[34] Delalić, A., Somun–Kapetanović, R., & Šabanović, E. (2017). POVERTY AND INEQUALITY IN BOSNIA AND HERZEGOVINA: INCOME OR CONSUMPTION APPROACH–DOES IT MATTER?. Sarajevo Business and Economics Review, 35, 53.

[35] Revenga, A. and Dooley, M. (2019). Income inequality beyond neoliberalism: Policies for more inclusive growth. In: G. Gertz and H. Kharas, ed., Beyond Neoliberalism: Insights from emerging markets. (online) The Brookings Institution.

[36] WID.world (2018). Gini index of national income. (Online) WID.World.

[37] WID.world (2019). Gini index of national income. (Online) WID.World.

[38] Benczur P.; Cseres-Gergely Zs.; Harasztosi P. EU-wide income inequality in the era of the Great Recession, JRC Working Papers in Economics and Finance, 2017/14, doi:10.2760/244655

[39] Thomson, H. and Bouzarovski, S. (2018). Addressing Energy Poverty in the European Union: State of Play and Action

[40] Trinomics (2016), Selecting Indicators to Measure Energy Poverty. https://ec.europa.eu/energy/sites/ener/files/documents/Selecting%20Indicators%20to%20Measure%20Energy%20Poverty.pdf

[41] Pye, S., Dobbins, A., Baffert, C., Brajković, J., Grgurev, I., Miglio, R., & Deane, P (2015). Energy poverty and vulnerable consumers in the energy sector across the EU: analysis of policies and measures. Published by INSIGHT_E.

[42] Gouveia, J.P., Palma, P., Simoes, S.G. (2019). Energy poverty vulnerability index: A multidimensional tool to identify hotspots for local action. Energy Reports, 5(2019) 187-201.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

[43] Tirado Herrero, S. and Bouzarovski, S. (2014). Energy Transitions and regional inequalities in energy poverty trends: Exploring the EU energy divide. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2537067

[44] OpenExp (2019). European Energy Poverty Index (EEPI): Assessing Member State's Progress in Alleviating the Domestic and Transport Energy Poverty Nexus. https://www.openexp.eu/european-energy-poverty-index-eepi

[45] Garcia-Peñalosa, C. (2018), Inequality in macroeconomic models. Revue de l'OFCE, 157 (2018).

[46] Zhang, X. (2019), Incorporating household survey data into a CGE model. https://www.pc.gov.au/research/supporting/household-data-cge-model

[47] Cockburn, J. (2001), Trade liberalisation and poverty in Nepal: A CGE micro simulation analysis.

[48] T. Rutherford, O. Shepotylo, D. Tarr (2005), The Impact on Russia of WTO Accession and The Doha Agenda: The importance of liberalization of barriers against foreign direct investment in services for growth and poverty, The World Bank

[49] Balasko, Y. & Tourinho, O.A. (2014), Factor proportionality in multiple households closed CGE models: theory and illustrations. Economic Theory Bulletin, 2014, vol. 2, issue 2, 119-136.

[50] CPB (2011), The labour market in CGE models

[51] Decaluwé, B, Patry, A., Savard, L., & Thorbecke, E. (1999b), Poverty Analysis Within a General Equilibrium Framework. June 1999. Working paper 9909 - CRÉFA 99-06. https://www.pep-net.org/sites/pep-net.org/files/typo3doc/pdf/9909.pdf

[52] Magnani, R. et al (2018), A Micro-Macro Simulation Model Applied to the French Economy: The Case of a Euro's Real Depreciation. The New Generation of Computable General Equilibrium Models: Modeling the Economy.

[53] Li, J. (2011), Dynamic Microsimulation for Public Policy Analysis.

[54] Capros P, De Vita A, Tasios N, et al. (2016) EU Reference scenario 2016 – Energy, transport and GHG emissions Trends to 2050. European Commission Directorate General for Energy, Directorate General for Climate Action and Directorate General for Mobility and Transport

[55] Fragkos P, Tasios N. et al (2017), Energy system impacts and policy implications of the European Intended Nationally Determined Contribution and low-carbon pathway to 2050, Energy Policy, Volume 100, Pages 216-226

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

[56] Harrison, Glenn W, Thomas F. Rutherford and David G. Tarr (2003), "Trade Liberalization, Poverty and Efficient Equity," Journal of Development Economics, 71, June, 97-128.

[57] Vandyck, Toon & Regemorter, Denise. (2014). Distributional and regional economic impact of energy taxes in Belgium. Energy Policy. 72. 190–203. 10.1016/j.enpol.2014.04.004.

[58] Thomas Rutherford, D. Tarr, (2004), "Poverty Effects of Russia's WTO Accession: modelling "real" households and endogenous productivity effects" The World Bank

[59] Rausch, S.; Metcalf, G. & Reilly, J. (2011), 'Distributional Impacts of Carbon Pricing: A General Equilibrium Approach with Micro-Data for Households', Energy Economics 33.

[60] IEA, World Energy Outlook, 2019, International Energy Agency, Paris

[61] European Commission, Ageing Report, 2018

[62] IRENA (2020), Renewable Power Generation Costs in 2019, International Renewable Energy Agency, Abu Dhabi

[63] Bachmann, R., Bechara, P., & Vonnahme, C. (2020). Occupational mobility in Europe: Extent, determinants and consequences. De Economist, 168(1), 79-108

[64] Fries-Tersch, A., Jones, M., Böök, B., de Keyser, L., Tugran, T. (2019) 2019 Annual Report on Intra-EU Labour Mobility. Final Report January 2020. European Commission

[65] Keeley, Brian (2015), "Why is income inequality rising?", in Income Inequality: The Gap between Rich and Poor, OECD Publishing, Paris

[66] Harrison A., J. McLaren and M. McMillan (2011). "Recent perspectives on trade and inequality", Annual Review of Economics, 3: 261–289

[67] Fragkos P., Paroussos L., 2018 Employment creation in EU related to renewables expansion Appl. Energy 230 935–45

[68] Revenga, A. and Dooley, M. (2019). Income inequality beyond neoliberalism: Policies for more inclusive growth. In: G. Gertz and H. Kharas, ed., Beyond Neoliberalism: Insights from emerging markets. (online) The Brookings Institution.

[69] World Bank. (2016). Poverty and Shared Prosperity 2016: Taking on Inequality. Washington, DC: World Bank.

[70] IMF (2014). IMF Policy Paper: Fiscal Policy and Income inequality. (online) Washington, D.C https://www.imf.org/external/np/pp/eng/2014/012314.pdf

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

[71] Paulus, A., H. Sutherland, and P. Tsakloglou, 2009, "The Distributional Impact of In-Kind Public Benefits in European Countries," EUROMOD Working Paper EM10/09 (Essex: University of Essex).

[72] Piketty, T., & Saez, E. (2013). Top incomes and the great recession: Recent evolutions and policy implications. IMF economic review, 61(3), 456-478.

[73] Norregaard, J. (2015). Taxing Immovable Property: Revenue Potential and Implementation Challenges. In Inequality and Fiscal Policy, ed. Clements, B., de Mooij, R., Gupta, S. and M. Keen. Washington, DC: International Monetary Fund.

[74] Benhabib, J., Bisin, A., & Zhu, S. (2011). The distribution of wealth and fiscal policy in economies with finitely lived agents. Econometrica, 79(1), 123-157.

[75] Piketty, T, 2011, On the long-run evolution of inheritance: France 1820-2050, Quarterly Journal of Economics, vol 126: 1071-1131.

[76] Schleich, J. (2019). Energy efficient technology adoption in low-income households in the European Union – What is the evidence? Energy Policy, 125, 196–206. doi:10.1016/j.enpol.2018.10.06

[77] ECN-TNO (2017), Fuel Poverty –Instruments and Approaches in the Netherlands, https://www.fes.de/index.php?eID=dumpFile&t=f&f=7775&token=2a2d8b598b5a3b56be9a215ead6508ca4cc0bc00

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Research paper 4: Reducing the decarbonisation burden for EU energy intensive industries

Authors: Panagiotis Fragkos, Kostas Fragkiadakis, Leonidas Paroussos

Status of the research paper: *The paper has been submitted for peer-review in the Energies journal*

Abstract: The issues of industrial competitiveness and carbon leakage are key topics of the climate policy debate in all major economies implementing ambitious climate policies, especially in the EU. The imposition of high carbon pricing impacts negatively the competitiveness of energy-intensive industries, inducing their relocation to countries without ambitious climate policies. Unilateral climate policy cannot directly impose carbon prices on foreign sources, but it can complement domestic emissions pricing with border carbon adjustment to reduce leakage and increase global cost-effectiveness of the mitigation effort. In the current study, we use an enhanced version of the multi-sectoral GEM-E3-FIT model to assess the risk of carbon leakage when the EU implement ambitious climate policies. It is found that total carbon leakage is around 25%, over the 2020-2050 period, when the EU acts alone implementing the EU Green Deal goals. The size and composition, in terms of GHG and energy intensities, of the group of regions undertaking emission reductions matter for carbon leakage. The paper finds that the leakage is significantly reduced when China joins the mitigation effort. This is attributed to both the market size of China and to the high energy and carbon intensity of its production. Chemicals and metals are the industries most prone to higher relocation to non-abating countries. We also find that border carbon adjustment can effectively reduce leakage and the adverse impacts on energy-intensive and trade-exposed industries in unilaterally abating countries. However, the scope for global cost savings is small. The main effect of border carbon adjustment is to shift the economic burden of emission reduction to non-abating countries through implicit changes in product prices.

5.1 Introduction

Climate change is particularly challenging for public policymakers, as the global nature of greenhouse gas (GHG) emissions makes unilateral emission reduction actions difficult to implement because the costs of abatement are borne primarily by the country taking action while the benefits of the policy are shared by all. This policy environment encourages free riding, increasing countries' reluctance to undertake potentially costly emission reductions because they fear that comparable measures will not be adopted by others (Carbone, Rivers 2017).

As the prospects for a global agreement on collective GHG emission reduction are weak and current climate pledges are not consistent with the ambitious Paris Agreement goals (Fragkos et al, 2020), individual countries are pushing for unilateral climate policy in the hope that other countries will follow suit (Bohringer et al, 2012). The fundamental drawback of unilateral action is that it forgoes large cost savings from "where-flexibility" (Weyant, 1999): To minimize global abatement cost, emissions should be reduced where it is cheapest worldwide, across regions and sectors. The imposition of unilateral climate

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

policies leading to differential carbon prices across countries indicates a large but unexploited potential for cost savings. In addition, unilateral carbon pricing in an open economy not only causes structural adjustment of domestic production and consumption but also affects its competitiveness in international markets, which drives international trade patterns through relative cost differences among countries. As a consequence, the global cost-effectiveness of emission reduction can be hampered by the so-called carbon leakage, i.e., the relocation of emissions to regions with no (or weaker) environmental regulation. There are two major intertwined channels contributing to carbon leakage, i) the energy channel, through changes in international fossil fuel prices, and ii) the industrial competitiveness channel (Paroussos et al, 2015). Leakage through the fossil fuel price channel occurs as reduced energy consumption in emission-constrained regions depress international fossil fuel prices, which in turn triggers additional fossil fuel consumption and emissions in non-abating countries. Leakage through the industrial competitiveness channel occurs as the production cost of energy-intensive and trade-exposed (EITE) industries in unilaterally abating countries increases compared to international competitors, which incentivizes the relocation of these industries abroad. The competitiveness channel amplifies adverse production and employment impacts for EITE industries in unilaterally regulating countries.

The macro-economic and industrial impacts of unilateral climate policies are commonly analyzed with computable general equilibrium (CGE) models, which complement theoretical analysis as they allow researchers to conduct counterfactual quantitative experiments that are grounded in microeconomic theory (Carbone and Rivers, 2017). Policymakers considering unilateral climate policies place a high focus on domestic economy and employment effects, assuming that other countries will not take comparable climate action. These domestic economic impacts are often referred to as "loss of competitiveness", which is a key factor for government decisions to avoid, delay, or weaken domestic climate policies; the literature refers to competitiveness in terms of changes in welfare, output, market share, export volume, terms of trade, or employment levels (Carbone and Rivers, 2017).

Concerns about the competitiveness of EITE industries are at the heart of climate policy debate in major economies implementing emission reduction policies. Recently, the EU Green Deal acknowledged the risk of carbon leakage, either because production may be transferred from the EU to other countries with lower climate ambition, or because EU products may be replaced by more carbon-intensive imports[21]. In case of persistent differences in levels of climate ambition worldwide, the European Commission proposes a Border Carbon Adjustment (BCA) mechanism, for selected sectors, to reduce the risk of leakage by ensuring that the price of imported products reflects more accurately their carbon content. The BCA mechanism imposes a tax on emissions embodied in imported goods and services from non-regulating countries in order to level the playing field between domestic and imported products with respect to carbon costs. With the right design, a BCAM could prevent carbon leakage, incentivize foreign producers to shift toward lower emission technologies, and exert pressure on trade partners to strengthen their climate action. The BCA should be designed to comply with World Trade Organization rules and other international obligations of the EU. While BCA has theoretical appeal on global cost efficiency grounds (Hoel 1991), it may cause adverse

[21] The European Green Deal, https://eur-lex.europa.eu/resource.html?uri=cellar:b828d165-1c22-11ea-8c1f-01aa75ed71a1.0002.02/DOC_1&format=PDF

"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"

distributional impacts. BCA can work as a substitute for strategic tariffs, shifting the economic burden of emission reduction from abating to non-abating countries (Böhringer, et al 2011). The burden shifting potential of BCA may trigger cooperation by non-abating countries, but it may also lead to detrimental trade conflicts, through retaliation measures.

The current study offers new insights on the risk of carbon leakage and industrial relocation in case of asymmetric climate policies across regions and provides an improved understanding of the sectoral and regional structure of leakage. The paper goes beyond existing literature by: 1) assessing for the first time the competitiveness impacts of the ambitious EU Green Deal targets towards climate neutrality by mid-century, 2) using an advanced version of the leading GEM-E3-FIT model with an enhanced representation of energy system and technologies required for climate neutrality, 3) exploring the impacts of first-mover coalitions conceptualising the most recent climate policy announcements of China aiming to achieve carbon neutrality by mid-century, thus ensuring high policy relevance of the analysis and 4) assessing the effectiveness of BCA mechanism in reducing carbon leakage and protecting the European EITE industries.

Our study proceeds as follows. Section 2 presents an overview of the issue, while Section 3 lays out the study design and methodological approach used. Section 4 discusses the key findings of the model-based assessment on carbon leakage and BCA measures. Section 5 concludes.

5.2 Overview

5.2.1 The European Industrial landscape

The industrial sector is a backbone of the European economy as it accounts for 68% of Europe's exports and private innovations (European Commission, 2019). About 17% of total value added in the EU comes from manufacturing, while industries create both direct and indirect jobs (i.e. in the supply chain of manufacturing activities). Industry provides 32 million jobs in the EU in 2018 (Eurostat). The European Commission (EC) acknowledges that EU industry is undergoing a deep transformation, based on the uptake of new technologies, changing conditions in international markets, the need for greater energy and resource efficiency, new business models, greater consumer demand for manufacturing activities being bundled with services (EC Juncker Plan, autumn 2017). EC plans revived or new key industry sectors, e.g. construction, steel, paper, green technologies and renewable energies, manufacturing and maritime shipping (EC Juncker Plan, autumn 2017). In addition, the COVID-19 pandemic and the restrictions imposed heavily impacted the global and EU manufacturing activities and disrupted the international value chains. The short-term effects of COVID are already evident in the European and global manufacturing activities, while the long-term impacts are difficult to assess, but some authors already point to economic changes related to localisation of production, remote working and changes in travel patterns.

In the process of economic and industrial restructuring in the EU, there are some major trends that shape the development. European industries will continue to face growing global competition in traditional energy-intensive industries, e.g. steel, cement, and chemicals. In addition, the EU will encounter global competition where new products enter into the market, e.g. e-vehicles, renewable technologies, batteries. Industrial policies and technological development are still too weakly coordinated, with large barriers of

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

moving from R&D to market phase in most EU Member States. As ETS carbon taxation increases by 2050, the European carbon and material intensive industries face increased risks of carbon leakage to non-abating countries. The EU foreign policy should secure access for EU countries to energy and mineral resources needed for many high-tech future products, e.g. rare earth mineral deposits. The European industrial policy should integrate key interlinkages with global megatrends, shaping global future developments, including automation, digitization, new business models, globalisation and climate change policies. The globalisation trend increases the competition of EU industries with their international competitors; in traditional industries, the EU competitiveness depends crucially on high labour costs and stringent environmental regulation, while increased innovation and R&D may increase European competitiveness in all high-tech branches. To ensure its long-term competitiveness in an increasingly globalised market, the EU industry can be transformed towards an "energy and resource efficiency" paradigm based on circular economy, uptake of low-carbon technologies and carriers (e.g. electrification of industrial processes, green hydrogen) and novel manufacturing principles, e.g. Industry 4.0, ICT based management. EU industrial policies should be aligned with overall economic, financing and education policies in order to foster industrial competitiveness, e.g. new business venture formation, more friendly framework conditions for entrepreneurial activities, support for firms' innovative activities, support business and innovation dynamics, better human resource reallocation and skills growth.

The energy intensive industries are characterized by strong economies of scale and high capital and energy intensities, as the processing of raw materials requires chemical conversions taking place at high temperatures or energy intensive breaking of chemical bonds. Such processes involve high fixed costs and have potential for significant energy efficiency and organizational economies of scale, which results in large scale processing plants. These plants require high upfront capital costs and are complicated to run as they are highly automated, often producing different qualities of products. The high upfront costs need to earned back in markets with large variations in prices and profit margins, resulting in uncertainty and long investment cycles. The recovery of capital costs depends on high capacity utilisation, implying that plants may keep operating at an overall loss as long as prices for industrial products are higher than variable production costs. These plants are very profitable during periods of high demand and high prices (Wesseling et al., 2017). Energy-intensive activities emit high amounts of GHG emissions due to their high energy requirements and the nature of the technological processes applied, often requiring carbon intensive fuels like coal.

Investment cycles for industrial sectors can typically range between 20 and 40 years. Plants are more regularly refurbished to increase productivity and improve energy efficiency. These cycles vary for different technologies, from 6 to 9 years for chemical facilities to 10–15 years for glass tanks and Blast Furnaces. The high scale, energy and capital intensity of energy-intensive activities results in increased barriers to market entry for new players, with new entrants often having to cooperate with or be absorbed by major established players. As a result of this, in most industrialised economies (including EU countries) brown field investments in existing factories are more typical to create new production capacity than building new factories (green field investments). Due to these barriers, many energy-intensive sectors are characterized by large multinationals that own plants around the world and may have a dominant market position. The European glass industry for example consists of more than 1,000 companies but more than 80% of the glass is produced by less than a dozen multinationals.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

5.2.2 European policies on carbon leakage

The concept of carbon leakage has been closely related with competitiveness in international markets in the discussion of unilateral climate policies (Aldy, 2017; De Cian et al., 2017). If a country or a coalition of countries implement ambitious environmental policies, e.g. by imposing high carbon pricing, while the rest of the world do not adopt such policies, energy-intensive manufacturing activities may relocate to non-abating regions in order to minimise their carbon-related production costs. This issue has received increasing focus in EU policy debate recently, especially as the EU Green Deal suggested the Border Carbon Adjustment Mechanism (BCAM) as a policy measure to minimise the risk of industrial relocation of European energy-intensive activities to non-EU regions. It should be noted that there are no indications that existing EU carbon pricing has led to carbon leakage (Zachmann, 2020), as the current EU carbon price remains at low levels and free allowances are given to energy intensive and trade-exposed industries.

Carbon leakage refers to the situation when for reasons of cost increases related to climate policies, businesses decide to transfer their production activities to other countries with laxer emission constraints and limited environmental regulations. This could lead to an increase in emissions outside the EU, thus reducing the climate policy effectiveness. The risk of carbon leakage is higher in certain energy-intensive industries, where energy costs represent a high share of their total production costs. Under the EU Emissions Trading System (EU ETS), industrial installations considered to be at significant risk of leakage receive special treatment to support their competitiveness in the form of receiving a higher share of free allowances compared to the other industrial installations. This policy will continue in phase 4 of EU ETS (2021-2030), but based on more stringent criteria and improved data. In phase 3 of EU ETS, a sector is considered to be at significant risk of carbon leakage if:

- direct and indirect costs induced by ETS pricing would increase production cost, calculated as a proportion of the gross value added, by at least 5%; and
- the sector's trade intensity with non-EU countries (imports and exports) is above 10%.

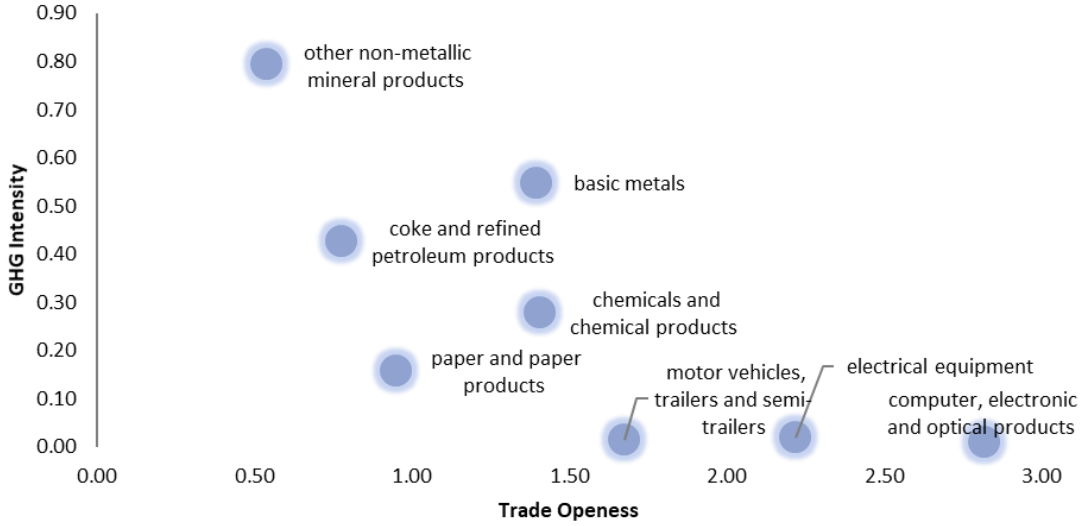
In addition, if only one of the above indicators for one sector is above 30%, then this sector is also deemed to be exposed to carbon leakage. In phase 3 of the EU ETS, the amount of free allocation for each ETS installation is calculated based on a formula where its production quantity (in tonnes of product) is multiplied with the benchmark value for that particular product (measured in emissions per tonne of product). Sectors exposed to a significant risk of carbon leakage in principle are eligible to receive free allocation at 100% of this quantity (e.g. metals, chemicals, cement, non-metallic minerals, paper and pulp). For installations in other sectors, not on the carbon leakage list[22], the free allocation is gradually reduced across phase 3 (80% in 2013, gradually reducing to reach 30% in 2020). Since the benchmarks are based on the performance of the most efficient installations, only the most efficient installations in each sector receive enough free allowances to cover all their needs. In phase 4 of EU ETS, free allocation will focus on sectors at the highest risk of relocating their production outside of the EU. Figure 23 presents the carbon leakage exposure for EU industrial sectors as a function of their GHG

[22] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:L:2019:120:FULL

"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"

intensity and trade openness. Basic metals, chemical products, non-metallic minerals, oil products, paper and pulp are the sectors more exposed to carbon leakage, while sectors like motor vehicles, electrical equipment and electronic products face lower relocation risks as they have significantly lower GHG intensity.*Figure 23*

Figure 23: Carbon leakage exposure as a function of trade openness and GHG intensity



The European Commission decision (2010/2/EU) lists the industrial sectors which are deemed to be exposed to a significant risk of carbon leakage, including the energy intensive industries producing chemical products, ferrous and non-ferrous metals, paper products, cement and other non-metallic minerals. The cost of energy in total production costs of these industries is on average four times higher than in the other industrial sectors (Paroussos et al, 2015). The power and transport sectors are mostly oriented to domestic markets and intra-EU trade with limited exchanges with non-EU regions. So, electricity supply and transport are not considered to be subject to high carbon leakage rates, unlike energy intensive industries which are strongly exposed to foreign trade competition.

Energy intensive industries accounted for about 7% of global GDP and 8% of global employment in 2015, but they account for about 60% of global energy used in the industrial sector, mostly in chemicals, ferrous and non-ferrous metals, cement, paper and pulp. The most important producers of energy intensive products are the EU, the USA, China, Korea, Mexico, Indonesia, Russia and Japan. Openness to foreign competition can be measured both in international and domestic markets as the ratio of exports to total output and as the ratio of product output used for domestic purposes to its total supply, respectively. The European production of metals, chemicals and non-metallic minerals is more exposed to foreign competition compared to other industries, both in domestic and foreign markets. It should be noted however that a large share of exports of chemicals represent non-energy intensive products such as pharmaceuticals, which do not face high increases in production costs due to carbon pricing.

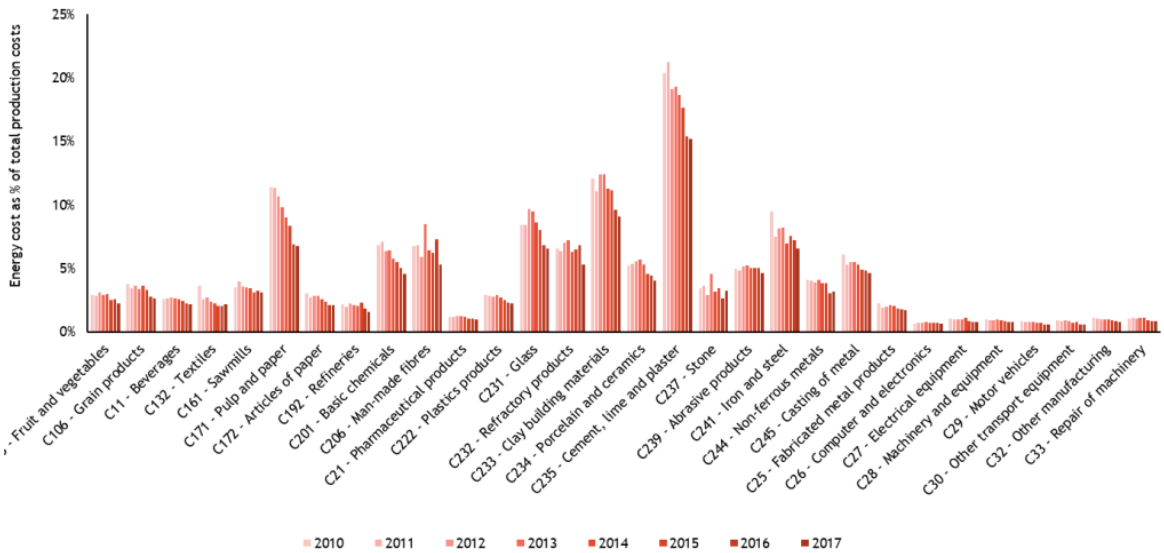
In addition to the degree of exposure to foreign competition, carbon leakage rates also depend on certain industrial conditions, such as: i) the easiness of industrial relocation given that high transportation costs usually cluster the markets into certain geographical areas; ii) the degree of vertical integration and specialization in relation to

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

other industrial and services activities which are not relocated; an example is the relations between metal industries and car manufacturing. The EU's main trading partners are China and the USA, followed by India, Russia, Turkey and Japan. Trade partners with good access and geographical proximity to the EU market and less ambitious climate policies (e.g. Russia, Turkey) can be considered the main economies toward which production could be relocated from the EU.

Figure 24 shows that energy costs as a share of total production costs declines from 2010 to 2017 for EU manufacturing sectors. The largest percentage point decline in cost share can be observed in the Pulp and Paper sector, in which costs fell from 11.4% in 2010 to a 6.7% share in 2017.

Figure 24: Average energy costs as a share of production costs for EU manufacturing sectors, Source: Study on energy prices, costs and their impact on industry and household



Source: Own calculations based on data from Eurostat SBS

Energy costs for the EU manufacturing sectors typically accounted for 1-10% of total production costs, while costs exceeded 10% for several sectors, including Cement, lime and plaster, building materials, pulp and paper, iron and steel, glass, basic chemicals. These energy intensive industrial sectors are most sensitive to energy prices, carbon taxation and cost changes. However, all these sectors experienced declining energy cost shares in recent years over 2010-2017. Among less energy intensive manufacturing sectors, energy costs typically constitute only 1-3% of their production costs and are therefore a relatively small cost component for businesses in these sectors, while energy costs represent less than 1% of production costs for sectors like Computer and electronics, Machinery and Equipment, Transport Equipment and Motor vehicles. Energy cost shares have fallen across all manufacturing sectors over 2010-2017, but even more steeply in recent years after 2014. Exploring the international dimension, the EU has energy cost shares comparable to those of most international trade partners, although there are differences by sectors and regions (European Commission, 2020). For example, the EU has a relatively high energy cost share in Iron and steel and Non-ferrous metals, but a low energy cost share in Refineries and Basic Chemicals.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

5.2.3 Policy Measures to protect domestic industries

There are several policy options available to reduce the adverse impacts of carbon pricing on Energy Intensive and Trade Exposed (EITE) industries facing reduced competitiveness in international markets. These can be classified in three categories which were discussed in detail in Droege et al., (2009) and Decian et al. (2017) and are summarised below:

Adjusting carbon costs at the border: These policy instruments adjust the carbon costs at the border of the jurisdiction implementing the carbon pricing scheme. The EU Green Deal communication suggests to adopt a BCA mechanism in order to protect the competitiveness of the most venerable European energy-intensive industries. This policy instrument aims to equalize the carbon costs on imports and exports in the jurisdiction implementing the carbon price through imposing the same carbon price on imports from non-regulated countries and rebating the carbon costs to exports to non-regulated countries. Another relevant instrument is the imposition of an EU-wide horizontal tax on carbon content, in the form of a carbon price levied on the consumption of goods regardless of their origin. While the measure is effective in reducing carbon leakage of EITE industries, it may lead to negative socio-economic outcomes in EU Member States.

Adjusting carbon costs upwards for non-domestic firms: These policy measures aim at increasing the carbon costs of firms outside the jurisdiction implementing the climate policy. This may take the form of sectoral agreements aiming to extend the participation of sectors or industries in climate change mitigation action by offering options such as technology transfers, research and development collaboration, etc. However, it is difficult to achieve a revision of existing multilateral trade rules with major trade partners, in particular to reach an agreement on cutting industrial subsidies.

Adjusting carbon costs downwards for domestic firms: These policy options seek to reduce the carbon related costs for domestic firms by maintaining a marginal abatement incentive equivalent to that if such measures are not introduced. This strategy can take various forms. For example, free allocation of tradable permits, e.g. under an Emission Trading System like the EU ETS, can relieve firms and industries from buying the emission permit but maintains the incentive to abate emissions. Carbon tax revenues can also be used to support investment (e.g. in clean energy innovation) that will reduce the cost of new, low-carbon and more efficient technologies. Environmental tax reforms aim to shift the target of taxation from labour or capital to polluting activities, while output based rebates returns the revenues generated by a carbon tax to industries in proportion to their output.

The Carbon Border Adjustment has currently received increasing focus in policy debates after the European Commission suggestion to introduce BCA as part of the EU Green Deal. Given the high policy relevance of BCA and the drawbacks of other anti-leakage policy options (especially with regard to their non-compliance with WTO trade rules), the current study largely focuses on the assessment of BCA as a policy measure to reduce the cost burden on energy-intensive and trade-exposed sectors, by imposing the EU carbon price on imported products from non-regulating countries.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

5.3 Methodology

5.3.1 The GEM-E3-FIT Modelling Framework

The GEM-E3-FIT model is a multiregional, multi-sectoral, recursive dynamic CGE model, which provides details on the macro-economy and its complex interactions with the environment and the energy system. GEM-E3-FIT simultaneously represents 46 regions (all EU member states are represented separately) and 51 sectors linked through endogenous bilateral trade flows and runs until 2050 with a 5-year time step. It is a comprehensive model of the global economy, covering the complex interlinkages between productive sectors, consumption, price formation of commodities, labour and capital, bilateral trade and investment dynamics. The economic agents are assumed to exhibit optimising behaviour while market derived prices are adjusted to clear markets, allowing for a consistent evaluation of distributional effects of policies. The model is dynamic, recursive over time, driven by accumulation of capital, equipment and knowledge and can quantify the macro-economic, employment and trade impacts of policies. GEM-E3-FIT allows for a consistent comparative analysis of policy scenarios since it ensures that in all scenarios the economic system remains in general equilibrium.

Industries operate within a perfect competition market regime and maximize profits. Production functions consider the possibilities of substitution between capital, labour, energy and materials in each production sector. Households demand, savings and labour supply are derived from utility maximization using a linear expenditure system (LES) formulation. Households receive income from labour supply and from holding shares in companies. Investment by sector is dynamic depending on adaptive anticipation of capital return and activity growth by sector. A distinctive feature of GEM-E3-FIT is the representation of imperfect labour markets through involuntary unemployment, simulated by an empirical labour supply equation that links through a negative correlation, wages and unemployment for five labour skills. The model formulates production technologies in an endogenous manner allowing for price-driven derivation of intermediate consumption and the services from capital and labour. A bottom-up approach is adopted to represent different power producing technologies. For the demand-side, the model formulates consumer behaviour and distinguishes between durable (equipment) and consumable goods and services. GEM-E3-FIT is calibrated using the GTAP dataset and national input-output tables that provide a comprehensive and self-consistent accounting of international trade, firms' production structures, households' consumption, gross fixed capital formation and sectoral value added.

GEM-E3-FIT model includes several features that go beyond a conventional CGE approach, allowing for an improved representation of the policy impacts on the economy and the society. In this respect, the model incorporates: a detailed and explicit representation of the financial sector, endogenous growth through R&D and learning-by-doing for low-carbon technologies, detailed modelling of energy system and related technologies and disaggregated representation of employment by skill. GEM-E3-FIT is extensively used as a tool for policy analysis and impact assessments, especially in the energy and climate policy fields by the European Commission and national governments (Capros et al., 2016; Fragkos et al., 2017). Additional details of the enhanced version of GEM-E3-FIT (as developed in INNOPATHS) can be found in Deliverable D4.1 of the INNOPATHS[23] project.

[23] https://innopaths.eu/publications/#project-deliverables

"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"

The following paragraphs describe the representation of international trade in GEM-E3-FIT, which is the key topic of the current study. All regions and sectors are linked through endogenous bilateral trade flows. Total demand of each sector is optimally allocated between domestic and imported goods, under the hypothesis that they are imperfect substitutes (Armington assumption)[24]. The supply mix is represented as a multi-level nested constant elasticity of substitution function: at the upper level, firms decide on the optimal mix between domestically produced and imported goods; at the next level the demand for imports is split by country of origin. Bilateral trade transactions by sector are endogenous in the GEM-E3-FIT model and depend on relative production costs, transportation costs and consumer preferences (as the latter have been captured by the national account statistics on trade). Each country buys and imports at the prices set by the supplying countries following their export supply behaviour. The buyer of the composite good (which is composed of domestic production and imports) seeks to minimise the total cost and decides the mix of imported and domestic products so that the marginal rate of substitution equals the ratio of domestic to imported product prices.

The optimal demand for domestic [1] and imported goods is obtained by the cost minimization problem of purchasing the composite good (1st level):

$$\mathrm{QD}_{j,\mathrm{r,t}} = \mathrm{QY}_{\mathrm{j,r,t}} \cdot \mathrm{AC}_{j,\mathrm{r,t}}^{\sigma x_{j,r,t}-1} \cdot \left(1-\delta_{j,\mathrm{r,t}}\right)^{\sigma x_{j,r,t}} \cdot \left(\frac{\mathrm{PY}_{j,\mathrm{r,t}}}{\mathrm{PD}_{j,\mathrm{r,t}}}\right)^{\sigma_{\mathrm{x_{j,r,t}}}} \quad [1]$$

$$QI_{j,r,t} = \mathrm{QY}_{j,r,t} \cdot AC_{j,r,t}^{\sigma x_{j,r,t}-1} \cdot \delta_{j,r,t}^{\sigma x_{j,r,t}} \cdot \left(\frac{PY_{j,r,t}}{PI_{j,r,t}}\right)^{\sigma x_{j,r,t}} \quad [2]$$

where:
j: sectors, r: countries, t: time,
$QY_{j,r,t}$: composite goods volume index, $PY_{j,r,t}$: composite goods price index,
$QD_{j,r,t}$: domestic goods volume index, $PD_{j,r,t}$: domestic goods price index,
$QI_{j,r,t}$: imported goods volume index, $PI_{j,r,t}$: imported goods price index,
$AC_{j,r,t}$: scale parameter in the Armington function,
$\delta_{j,r,t}$: share parameter estimated from the base year data related with the value shares of $QD_{j,r,t}$ and $QI_{j,r,t}$ in the demand for composite good $Y_{j,r,t}$,
$\sigma x_{j,r,t}$: the Armington elasticity between imported and domestically produced goods.

At the 2nd level the buyer seeks to minimise the cost of imported goods by choosing the optimal mix of imports by origin (Paroussos et al, 2015[25]):

$$QIM_{j,r,s,t=}\ QI_{j,r,t} \cdot \left(\beta_{j,r,s,t} \cdot \frac{PI_{j,r,t}}{PIM_{j,r,s,t}}\right)^{\sigma m_{j,r,t}} \quad [3]$$

where:
$QIM_{j,r,s,t}$: imported goods of country r from the country s volume index,
$PIM_{j,r,s,t}$: imported goods of country r from the country s price index,
$\beta_{j,r,s,t}$: share parameter estimated from the base year data related with the value shares of imported goods by origin.

[24] Armington Paul S., 1969, A Theory of Demand for Products Distinguished by Place of Production. IMF Staff Papers, 1969. 16(1): p. 159-178.

[25] Paroussos, L., Fragkos, P., Capros, P., Fragkiadakis, K., 2015, Assessment of carbon leakage through the industry channel: The EU perspective, Technological Forecasting and Social Change, Volume 90, Part A, January 2015, Pages 204-219

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

$\sigma m_{j,r,t}$: the Armington elasticity among imported goods by origin.

Table 9 contains the upper-level Armington elasticity values used in GEM-E3-FIT, which differ among sectors, but are identical for all countries /regions. Homogeneous products, like crude oil, are assumed to have higher elasticity values relative to other goods.

Table 9: Armington elasticities in various sectors

	σx	σm		σx	σm
Transport	1.90	3.80	Coal	3.05	6.10
Construction	1.90	3.80	Consumer Goods	3.21	6.43
Non Market Services	1.90	3.80	Chemical Products	3.30	6.60
Market Services	2.03	4.06	Transport equipment	3.55	7.10
Oil products	2.10	4.20	Electric Vehicles	3.55	7.10
Gas	2.80	5.60	Non-ferrous metals	3.98	7.95
Power Supply	2.80	5.60	Equipment goods	4.05	8.10
Ferrous metals	2.95	5.90	Batteries	4.05	8.10
Paper Products	2.95	5.90	Electronic Goods	4.08	8.15
Agriculture	3.03	6.07	Crude Oil	5.20	10.40

5.3.2 Study and scenario design

The study aims to assess the macro-economic and industrial implications of unilateral climate policy and evaluate possible measures to reduce the cost burden on certain industrial sectors, which are energy-intensive and are strongly exposed to foreign competition. In particular, the potential relocation of energy intensive manufacturing is explored in case that the EU unilaterally increases its emission reduction targets in line with the EU Green Deal and its long-term climate neutrality strategy. Other climate coalitions are also explored, assuming that China joins the ambitious EU mitigation effort reflecting the recent Chinese commitment towards carbon neutrality by 2060. Detailed descriptions of the alternative policy scenarios explored in the study are provided below.

The **Reference scenario** is a projection for the global economic and energy system evolution based on historical and current trends and scientific expertise on growth patterns, technical progress, labour productivity and energy and climate policies. The Reference scenario represents the benchmark against which alternative scenarios are compared to evaluate their impacts. Socio-economic developments of the Reference scenario replicate (IEA, WEO 2019) assumptions, while socio-economic assumptions for the Eu are based on the recent Ageing Report of the European Commission (EC, 2018).

In the Reference scenario, already adopted climate policies and pledges, including Nationally Determined Contributions (NDCs) are implemented by 2030. After 2030, no additional efforts to reduce GHG emissions is assumed. In modelling terms, this means that the carbon prices resulting from NDC targets in 2030 are kept constant until 2050. The scenario represents a lack of ambition in the international climate policy landscape, while most countries do not establish carbon pricing regimes (with the exception of EU ETS). International fossil fuel prices follow the trajectory of (IEA, WEO 2019). The costs

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

of power generation and other energy-related technologies are calibrated to (IRENA, 2020) findings, while technology progress is included for low-carbon technologies. As model results crucially depend on the adopted carbon revenue recycling scheme, we assume that ETS carbon revenues are recycled through the public budget.

Table 10: NDC emission targets included in the Reference scenario

Country	NDC emission targets	Energy-related NDC targets in 2030
EU28	-40% GHG in 2030 relative to 1990	30% RES in gross final demand
China	-60% (-65%) CO2 intensity in 2030 rel. 2005	20% Non-fossil in primary energy
India	-33% (-35%) CO2 intensity from 2005	40% Non-fossil in power capacity
USA	-26% (-28%) GHG in 2025 relative to 2005	
Canada	-30% GHGs in 2030 from 2005	
Japan	−26% GHGs in 2030 from 2013	20–22% Nuclear and 22–24% RES share in electricity in 2030
Brazil	−43% GHGs in 2030 from 2005	
Russia	25-30% below 1990 levels by 2030	
S. Korea	37% below Business as Usual (BAU) by 2030	
S. Africa	Peak GHG emissions in 2025 and plateau for a decade	

The **2DEG scenario** is consistent with the 2ºC temperature target as included in the Paris Agreement. In line with (Mc Collum et al, 2018), the global cumulative CO_2 budget is used as proxy for the temperature target. A universal carbon price is implemented across regions and sectors from 2020 onwards to reach the CO_2 budget of 1000 $GtCO_2$ by 2050, thus ensuring that the temperature increase relative to pre-industrial levels will stay well-below 2ºC. As the stringency of the mitigation target increases over time, the global carbon tax grows from 80$/tnCO2 in 2030 to about 350$/tnCO2 in 2050. The contribution of each country in global CO_2 reductions is determined by equal marginal abatement costs across countries Therefore, the 2DEG scenario represents the solution that meets the global carbon budget constraint with the minimum costs through equalisation of marginal abatement costs across regions and sectors.

The **"EUGD-Alone"** scenario assumes that the EU unilaterally adopts ambitious policies in order to achieve the EU Green Deal targets of GHG emission reduction of 55% in 2030 relative to 1990 and prepare the ground for the transition to climate neutrality by mid-century. As the EU Green Deal does not separately set a target for ETS and non-ETS, an EU-wide uniform carbon price is used from 2025 onwards. Energy system restructuring is induced by a combination of market and non-market policy drivers, including ambitious technology standards, subsidies to perform insulation in buildings, high carbon pricing, reduced risks for clean energy investment, enhanced electrification of energy and mobility services, subsidies for low-carbon Innovation and uptake of disruptive mitigation options that are required for climate neutrality (e.g. Carbon Capture Use and Storage, green hydrogen, production of clean synthetic fuels from RES-based

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

electricity). In contrast, non-EU countries follow the Reference policy setting and thus they meet their NDCs in 2030 and do not increase their policy ambition beyond 2030.

As the EU is actively signalling its intention to adopt ambitious climate measures with potentially adverse impacts on European energy-intensive industries, the BCA instrument can complement domestic carbon pricing, so that import tariffs mimic the domestic emission price on the carbon content of all goods that are not regulated in the countries of origin. The **"EUGD-BCA" scenario** explores the socio-economic and industrial implications of implementing EU-wide BCA mechanism on imports building on "EUGD-Alone" scenario assumptions, but additionally assuming that the BCAM is aligned with the EU ETS carbon pricing and applies only to those products subject to the ETS (e.g. energy-intensive industries). Imported goods from non-EU regions are taxed according to their carbon content, which is calculated accounting only for the direct GHG emissions. Tariff rates are differentiated by country, based on carbon flow information by GTAP to determine country- and sector-specific carbon coefficients. The revenues from BCA tariffs are directed to the general revenues of the abating country. Export rebates contribute to the cost-effectiveness of BCA since they avoid losing market shares in foreign markets. However, export rebates may constitute a subsidy under the WTO's Agreement on Subsidies and Countervailing Measures (Cosbey et al 2012) and are thus difficult to be implemented. The scenario assumes no retaliation measures from major trade partners. A variant of the BCA scenario explores the impacts of using BCA revenues to reduce social security contributions **("EUGD-BCA-REC" scenario**).

Carbon leakage and the importance of BCA as a complementary anti-leakage measure depends on the size of the abatement coalition and the ambition of the emission reduction target. Therefore, we also investigate scenarios with larger climate coalitions. In the **"EUGD-CHN"** scenario, the EU and China join policy efforts and pursue in common an ambitious emission reduction effort. This scenario reflects the recent policy announcements by the EU and China, aiming towards a carbon-neutral transition by 2050 and 2060 respectively. In particular, the joint emission reduction effort of the EU and China is equal to the aggregate emission reductions achieved by the EU (in the EUGD-Alone scenario) and China (in the 2DEG scenario). The energy system decarbonisation is triggered by the imposition of a uniform carbon price, which constantly increases from 2025 onwards in order to achieve the ambitious EU-China emission reduction target. Other countries follow the same policies as in the Reference scenario.

Table 11: Scenario description

	Scenario Description	EU Climate target	Non-EU climate targets
REF	Reference scenario	Meets the EU NDC	All countries meet their NDCs in 2030, policy ambition does not increase beyond 2030
2DEG	Decarbonisation to 2ºC with all options available	All countries adopt ambitious climate policies/universal carbon pricing to meet the 2ºC temperature target	
EUGD_Alone	EU meets the EU Green Deal Targets by 2030 and 2050	EU achieves 55/90% reduction in 2030/ 2050 from 1990	Non-EU countries meet their NDCs in 2030, policy ambition does not increase beyond 2030
EUGD_BCA	Green Deal Targets are met, BCA is implemented	EU achieves 55/90% reduction in 2030/ 2050 from 1990	Non-EU countries meet their NDCs in 2030, policy ambition does not increase beyond 2030

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

EUGD_BCA_REC	As EUGD_BCA but BCA revenues are used to reduce social security contributions	EU achieves 55/90% reduction in 2030/ 2050 from 1990	Non-EU countries meet their NDCs in 2030, policy ambition does not increase beyond 2030
EUGD-CHN	EU and China adopt ambitious climate policies	EU achieves 55/90% reduction in 2030/ 2050 from 1990	Countries do not intensify policy ambition beyond 2030; China develops along a 2DEG trajectory

5.4 Scenario Results

The section explores the socio-economic and industrial impacts of asymmetric climate policies and possible protective measures to reduce the cost burden and relocation of energy-intensive and trade-exposed industries, in particular focusing on BCAM.

5.4.1 Impacts of uniletaral ambitious European climate policies

During 2020, the European Commission proposed a new plan to increase its GHG emission reduction target for 2030, accompanied with the long-term goal to achieve climate neutrality by 2050. This proposal forms the basis of the EUGD-Alone Scenario, which meets the ambitious GHG reduction targets of 55% in 2030 and 90% in 2050 relative to 1990 levels mostly through an extensive transformation of the energy system. As the EU Green Deal does not set sectoral targets, an EU-wide uniform carbon price is used in the model, which reaches 75 $/tnCO2 in 2030 and 590 $/tnCO2 in 2030 indicating the increasing marginal abatement effort and difficulty in fully decarbonizing the EU energy system, especially in hard-to-abate sectors with limited access to technological mitigation options, including energy intensive industries and freight transport. The high carbon price drives a large-scale reduction in GHG emissions in order to achieve the Green Deal targets, as EU GHG emissions decline to about 575 Mt CO_2 in 2050, compared to 2350 Mt CO_2 in the Reference scenario, i.e. a reduction of 75% Most of this reduction is achieved through energy system decarbonisation, with extensive emission reductions projected both in energy demand and supply. Industrial CO_2 emissions decline significantly from Reference levels, as the decarbonisation of the European industrial system is achieved through a combination of large-scale energy efficiency improvements, electrification of industrial processes and fuel switch towards energy products with low or zero carbon intensity, e.g. biomass and green hydrogen, while domestic industrial activity is also reduced, as a part of energy-intensive manufacturing is relocated to countries that do not apply carbon pricing.

Figure 25 shows that all sectors and GHGs contribute to the ambitious EU emission reduction effort, but about 73% of the overall mitigation effort depends on the decline of CO_2 emissions. The latter is largely driven by energy system restructuring both on energy supply but also on energy demand sectors (mostly in transport). The European industrial sector accounts for about 25% of the overall EU mitigation effort relative to the Reference scenario, with large reduction of CO_2 emissions related to energy combustion and industrial processes.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

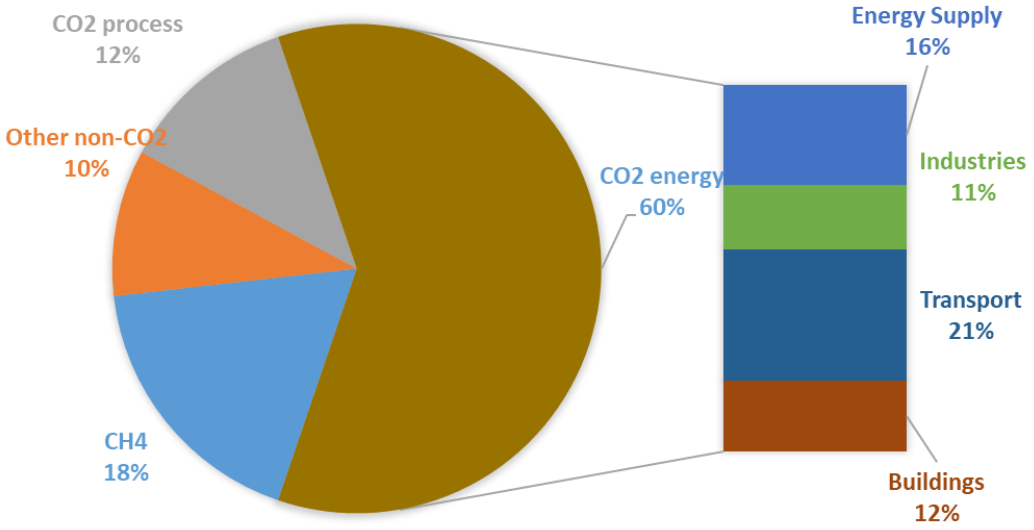


Figure 25: Distribution of the EU GHG mitigation effort by sector in the EUGD-Alone relative to Reference scenario in 2050

The energy system decarbonisation is a capital-intensive process characterised by the transition towards energy efficiency and low-carbon technologies, which require high upfront investment costs, but result in reduced operation and fuel costs in the longer term. A strict financial closure is adopted in the CGE modelling framework where investments are constrained by available savings and any additional investment plan needs to be financed by reallocating existing capital resources, leading to crowding-out of productive investment in other sectors. Therefore, the increased demand for financing the large-scale investments required for energy system transformation would increase the cost of capital with negative implications throughout the economy. The high carbon pricing imposed in the EU increases the production costs of energy and carbon intensive processes, while the costs for low and zero-carbon technologies decline as a result of their increased uptake (learning-by-doing). However, as non-EU countries do not intensify their climate policy ambition, the non-EU market demand for clean energy technologies remains relatively small; this implies that the potential export benefits from a more competitive EU position in low-carbon manufacturing are limited. In the EUGD-Alone Scenario, the driving factor for carbon leakage and industrial relocation to non-abating countries is the change in production costs of carbon intensive sectors through higher carbon prices.

As the EU unilaterally adopts ambitious climate policies in the EUGD-Alone scenario, GHG emissions outside the EU increase as energy and carbon intensive industries are relocated to non-abating countries and domestically produced goods are substituted by imported goods. The cumulative carbon leakage[26] is estimated at 24.6% with EU economy-wide GHG emissions declining by about 24 Gt cumulatively over 2025-2050, while non-EU emissions increase by about 5.9 Gt relative to the Reference scenario. The carbon leakage rate increases over time following the increase in the carbon

[26] Carbon leakage rate is calculated as the ratio of increased emissions in non-abating countries relative to Reference scenario over the amount of emission reductions in countries adopting ambitious climate policies

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

price differential between countries compared to the Reference scenario. The regions where carbon leakage occurs are Russia, Rest of World, China, India and the United States which mainly increase emissions in the EU-GD-Alone scenario from Reference levels (Figure 26). Low transportation costs to the EU market favour Russia and Turkey, while China and India have sufficient production capacities at low cost and relatively high energy and carbon intensities inducing higher increase in emissions (hence higher carbon leakage). It should be noted that the industrial relocation to the different countries is not proportional to the changes in GHG emissions as each country is characterised by different GHG intensities (e.g. one tonne of steel produced in the USA emits lowers GHG emissions than in India).

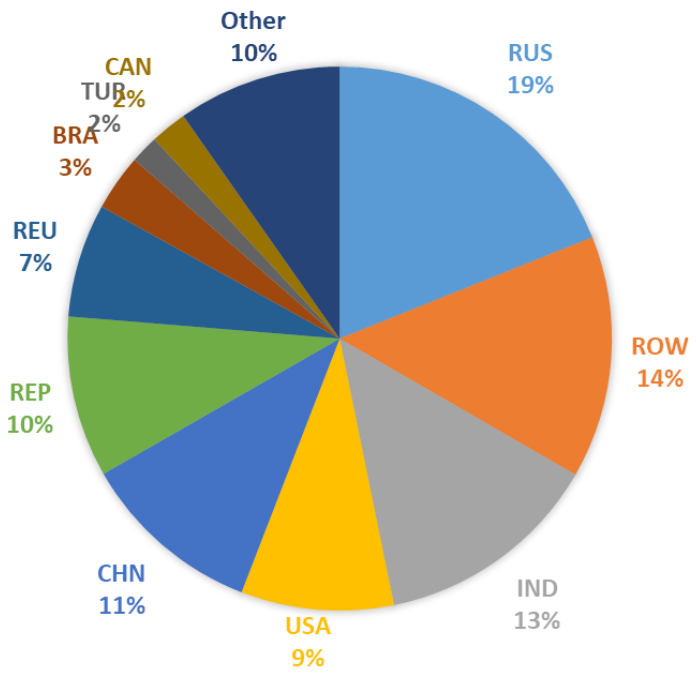


Figure 26: Regional decomposition of carbon leakage in EUGD-Alone over 2020-2050

The sectoral distribution of carbon leakage is presented in Figure 27. Given their high carbon intensities and openness to trade ratios, the sectors that are most vulnerable to carbon leakage are chemicals, non-metallic minerals, metals and air transport. The importance of sectoral leakage changes over time as the energy system is gradually decarbonised. An interesting finding is that carbon leakage occurs also indirectly through electricity-related emissions; the relocation of industrial activities to non-EU countries would lead to increased demand and production of electricity and thus higher carbon emissions in non-EU countries, especially as their power mix is still dominated by fossil fuels in the EUGD-Alone scenario. GHG emissions from refineries increase in most non-EU countries driven by the increased demand for oil products required to fuel industrial activities. However, in other countries refinery emissions decline as the electrification of the EU energy services reduces the aggregate demand for refined oil products.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

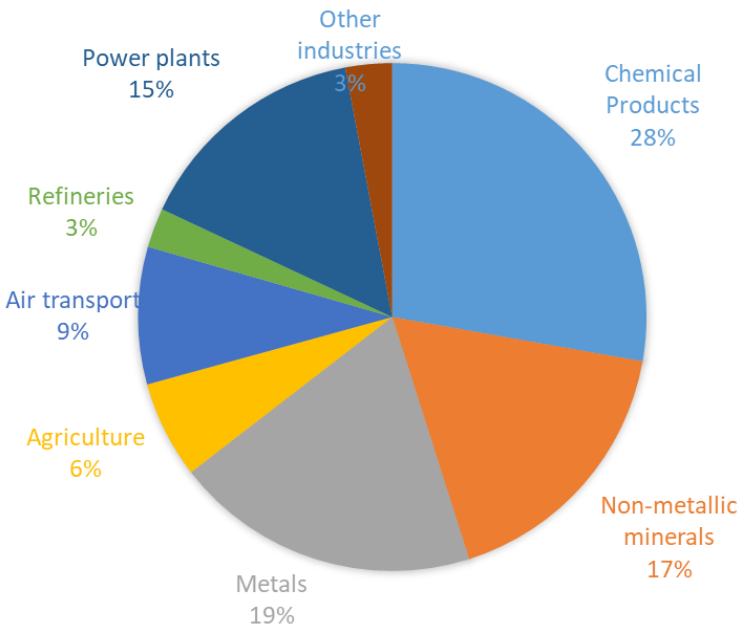


Figure 27: Sectoral decomposition of carbon leakage in EUGD-Alone over 2020-2050

The numerical simulations in this research study, in agreement with the literature, find that the net effect of high carbon pricing on economic activity is negative, as higher costs for energy services increase production costs and depress demand, in the presence of crowding-out effects (as analysed before). If carbon pricing applies unilaterally in an open economy, its competitiveness in international markets weakens implying further reduction of domestic activity, as parts of domestic industrial production is substituted by foreign activity which eventually emits more GHGs, as it is not subject to carbon pricing. Therefore, carbon prices are less effective than initially expected and carbon leakage occurs. The projections using the macro-economic GEM-E3-FIT model confirm that the unilateral application of high carbon pricing would result in GDP and consumption losses in the EU compared to Reference scenario. The EU has a strong low-carbon innovation base and industrial know how so as to build domestically a large part of the clean energy technologies (Karkatsoulis et al, 2016), but the corresponding activity increase is not sufficiently high to offset the activity depressing effects stemming from higher costs and prices and from the relocation of industrial activity to non-abating countries.

According to the model results, the cumulative EU GDP losses in the EUGD-Alone scenario over the period 2025-2050 are 1% below reference scenario GDP. As the carbon price differential between the two scenarios increases over time, EU GDP losses follow the same trend (Figure 28). The countries which do not apply additional carbon pricing relative to the reference scenario get activity benefits owing to their increased competitiveness, but also get activity losses because demand for their products declines in the EU, which experiences depressive effects on domestic demand due to the high carbon pricing. The net effect on GDP of non-abating countries is small, either slightly positive or slightly negative. The net effect on global GDP is slightly negative in all climate action scenarios as compared to the Reference scenario as a result of carbon pricing application.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

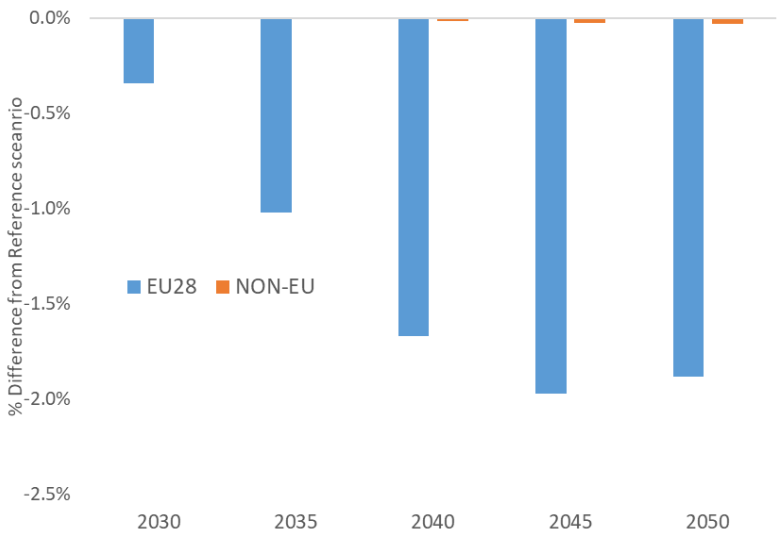


Figure 28: GDP implications of EUGD-Alone relative to Reference scenario

Demand for energy intensive products tends to decrease in countries applying carbon pricing because of increased production costs and despite their participation in building the clean energy related investment (e.g. metals contribute to wind turbine manufacturing and installation). The reduction in domestic EU production of energy intensive industries is also driven by the worsening of their international competitiveness, induced by the unilateral application of high carbon pricing. The degree of exposure of these industries to foreign trade is a critical factor influencing industrial relocation.

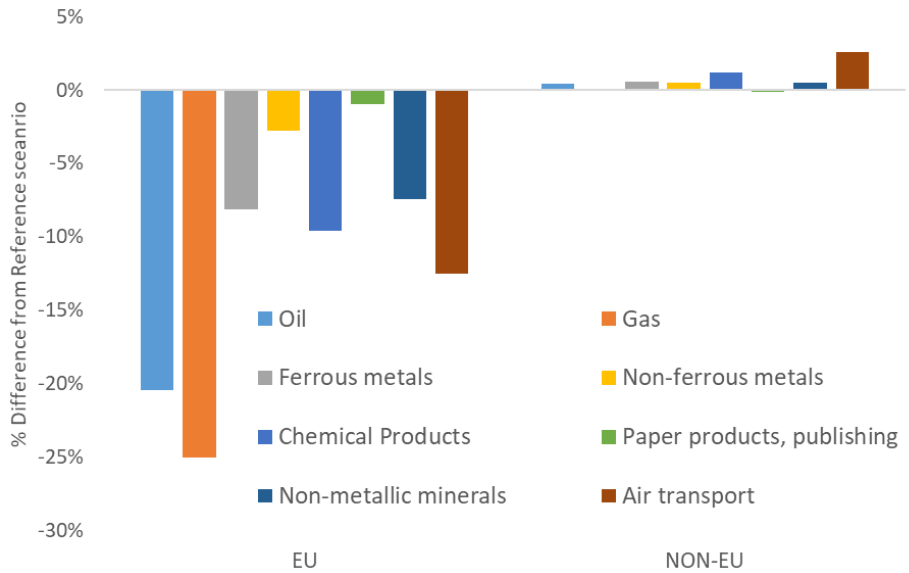


Figure 29: Cumulative changes in sectoral production in EUGD-Alone relative to the Reference scenario in EU and non-EU regions over 2025-2050

Figure 29 shows that the unilateral application of high carbon pricing impacts negatively the domestic industrial production in the EU. Energy system decarbonisation has profound negative impacts for the EU fossil fuel supply industries, which register a large activity reduction due to the reduced consumption of fossil fuels (oil, gas and coal). A large activity reduction is also projected for the domestic production of ferrous metals

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

and chemicals (between 8-10%), while the decline is lower in other industrial sectors, as cement, building materials and paper are less traded. Part of the decreased activity is relocated to non-EU countries that do not apply ambitious climate policies. An important observation is that the amount of industrial production decreased in the EU is higher than the amount of production increased in non-abating regions, because global demand for energy intensive products overall decreases from Reference levels, as restructuring towards less energy intensive products takes place induced by the implementation of climate policies in the EU. The sectors of chemicals and metals, as being more exposed to foreign competition, bear higher relocation impacts than cement and other building materials which due to high transportation costs need to be located close to consumption.

Table 12: Impacts of EUGD_Alone on industrial production over 2025-2050

Change from Reference over 2025-2050 (in bn Euro 2010)	EU production	Non-EU production
Oil	-3272	559
Gas	-142	5
Ferrous metals	-1103	795
Non-ferrous metals	-251	419
Chemical Products	-2265	1803
Paper products, publishing	-153	63
Non-metallic minerals	-1107	689
Air transport	-1206	914

Industrial leakage by sector is measured as the ratio of the amount of emission increases in non-abating over the amount of emissions reduced in the regions pursuing climate action. The leakage rate is projected to be particularly high for energy-intensive industrial sectors, in particular for metals and chemicals, as a large part of the European production is relocated to non-abating regions, which have a considerably higher carbon intensity relative to the EU, as their energy mix is still dominated by fossil fuels in the EUGD-Alone scenario. Industrial leakage rates as estimated by GEM-E3-FIT range from less than 5% for non-energy intensive production up to 70-80% for chemicals and metals, which are highly exposed to foreign competition and are relocated to countries with considerably higher carbon intensity than the EU (e.g. China, India, Russia). A large share of increased emissions in non-abating countries come from power generation, due to the increased electricity demand from industries and their fossil-based power supply system. This means that the overall leakage rates could be reduced if emission reduction measures focusing on power generation could be adopted in non-abating countries.

5.4.2 Impacts of joint EU-China ambitious climate action

When China and the EU jointly implement ambitious climate policies and apply high carbon pricing, the rate of carbon leakage is significantly reduced. The European and Chinese cumulative GHG emissions are reduced by about 129 Gt CO_2 relative to Reference scenario over 2020-2050. In the same period, GHG emissions in non-abating regions increase by 7.7 Gt CO_2 relative to Reference levels, indicating a carbon leakage rate of 6%, mostly in India, Russia and Rest of world region (Figure 30). The leakage rate

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

is significantly lower relative to the EUGD_Alone scenario, as Chinese emissions are much higher than the EU's and about 85% of the overall mitigation effort in the EUGD-China scenario is implemented in China (and only 15% in the EU). Therefore, the size of the countries that participate in joint emission reduction efforts matters a lot for the carbon leakage, as a larger country size implies lower carbon leakage rates. In addition, the imposition of common carbon price is more effective in reducing emissions in countries with high energy and carbon intensity, such as China. Modelling outcomes suggest that carbon leakage can effectively decline in case that the climate coalition includes countries with high carbon intensity and with low industrial production costs. For example, the increased energy costs in China (but starting from a low base) due to high carbon pricing have smaller effects on its relative competitiveness than a case where similar cost increases take place in a country with high industrial costs.

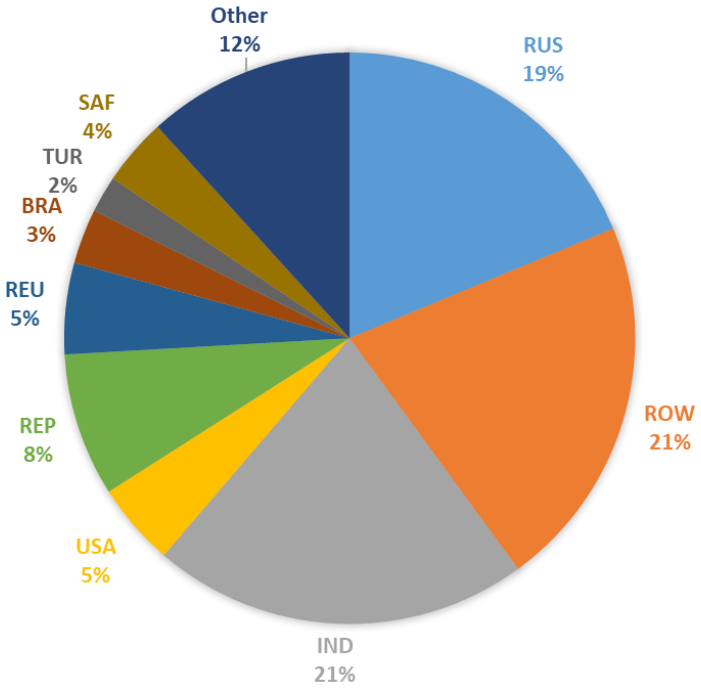


Figure 30: Regional decomposition of carbon leakage in EUGD-China over 2020-2050

Model-based results show that the global demand for energy intensive products (e.g. metals, cement) decreases in climate policy scenarios relative to Reference, due to the economic restructuring towards less energy intensive products and services as a result of high carbon pricing. This economic shifting reduces the carbon leakage rate. The sectors of chemicals, metals and non-metallic minerals are more exposed to foreign competition and bear higher relocation impacts than the other industrial sectors, which due to high transportation costs need to be located close to consumption.

Table 13 presents the regional impacts of the EUGD-China scenario on industrial activity and shows that regulating countries experience activity losses in energy intensive industries relative to Reference scenario. The losses are particularly high in the oil supply sector, but also in the production of (ferrous and non-ferrous) metals and chemicals, as cement, building materials and paper are less traded. The decrease in energy intensive industrial production takes place in both EU and China and part of the decreased activity

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

is relocated to countries not applying carbon pricing. Model-based outcomes show that the relative competitiveness and production shares of countries applying high carbon pricing (EU, China) in energy-intensive industrial production change in the scenario. For example, the imposition of common carbon price would result in higher relative increase in Chinese production costs compared to EU, and thus the competitiveness of European energy-intensive industries improves relative to Chinese industries. This means that energy-intensive industrial production declines more strongly in China (Table 13) and the Chinese economy encounters higher cost impacts than the EU. It should be noted that in the EUGD-China scenario, the sum of industrial production is lower from Reference levels in all energy intensive sectors . In addition, the activity impacts are larger in China with its GDP declining by 1.6% over 2020-2050 (with EU GDP declining by only 0.7%), due to the current high energy and carbon intensity of the Chinese economy and the large-scale reduction of Chinese energy-intensive industrial production, as the impact of carbon pricing is higher on low-cost industrial producers such as China

Table 13: Impacts of EUGD_China on industrial production over 2025-2050

Production Change from Reference over 2025-2050 (in bn Euro 2010)	**EU**	**China**	**Non- abating countries**
Oil	-2620	-4642	701
Gas	-115	-30	14
Ferrous metals	-290	-4901	2710
Non-ferrous metals	52	-1907	1155
Chemical Products	-1214	-3558	2401
Paper products, publishing	-128	-239	87
Non-metallic minerals	-546	-4282	1748
Air transport	-794	-122	580

The relocation of industrial manufacturing activities to non-abating countries leads to an increase in their energy and electricity consumption. As electricity trade across regions is minimal, this would also result in increased domestic production of electricity and therefore higher CO_2 emissions in non-abating countries, in particular as their power generation mix is dominated by fossil fuels. The increased emissions from power generation in non-abating countries are not related to changes in fossil fuel prices and the energy market channel, but are a direct consequence of industrial relocation, thus it is part of the industrial competitiveness channel.

5.4.3 How effective is the Border Carbon Adjustment?

As energy intensive industries are the most vulnerable to relocation away from the EU, policy makers explore measures to reduce the cost burden when ambitious climate policies are applied. The European Commission considers a Border Carbon Adjustment Mechanism (BCAM) to protect the competitiveness of European industries as part of the EU Green Deal. The main principles of a BCAM are relatively well-defined and are already part of the current policy debate in the EU. The BCAM is used to level the playing field between domestic and imported products with respect to carbon costs. With the right design, a BCAM could prevent carbon leakage, incentivise non-EU industries to shift

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

toward lower emission technologies, and exert pressure on trade partners to strengthen environmental regulations. In the EUGD-Alone scenario, the BCAM is aligned with the EU ETS carbon pricing entailing a similar coverage of products and the requirement for importers to purchase carbon allowances at prices equal to the EU ETS. This policy instrument targets the carbon content of imported goods that fall under the EU ETS sectoral classification. The EU ETS carbon price is applied to imported goods from non-EU countries whose carbon intensity exceeds a certain threshold, which is proxied with the notion of the Best Available Technology (BAT). The scenario does not assume direct participation of non-EU industries to the EU ETS, but the ETS carbon price is simulated as a tax, which is paid by economic operators at the port of entry in European borders. Essentially, the mechanism imposes an additional cost on non-EU goods based on the difference between the EU carbon intensity benchmark and the intensity of the sector and country of origin. The benchmark by sector is calculated using the technology with the lowest carbon intensity across EU Member States. The BCAM revenues are recycled through the public budget, while no retaliation is assumed by non-EU countries[27].

As the BCAM captures the regional differences in carbon intensities and the cost increases induced by the ETS price, this instrument is very effective in mitigating carbon leakage, which is found to decline from 25% in the EUGD-Alone to less than 4% (with the USA and China accounting for most of this leakage). The imposition of BCAM increases the cost of imported industrial products in the EU, thus resulting in a reduction of EU imports by 1.5% cumulatively over the period 2025-2050 (Figure 31). However, this instrument is not designed to support the competitiveness of European industries in international markets, as exported goods do not receive any compensation for their higher production cost due to ETS carbon pricing as a direct intervention would be non-WTO compliant. Therefore, the GEM-E3-FIT results show limited impacts of the scenario on European exports.

The recycling scheme used for the ETS and BCAM revenues greatly affects the socio-economic impacts of the policy measure. When there is no recycling of revenues, the implementation of BCAM instrument results in a slightly negative impact on EU activity (with GDP declining by 0.06% over 2025-2050 relative to EUGD-Alone) as it increases the costs of imported products which is then diffused to domestic production and consumption through product value chains and complex inter-industrial relations. Additional taxes imposed on imported products further increase production costs of EU-based industries and reduce real disposable income for households. The negative impact on activity is found both in EU and non-EU countries as the imposition of the tax increases frictions in the economy.

The recycling of BCAM revenues towards reducing social security contributions would reduce labour costs leading to the creation of additional jobs, with EU employment increasing by 0.3% relative to the EUGD-BCA scenario. The increased labour income drives up private consumption and GDP, while also being beneficial for the EU trade-balance. Our research also shows that BCAM is resilient to potential counteracting measures by non-EU competitors, as the low carbon intensity of the EU products leaves little room for significant cost increases in its exported goods if a retaliation tax is applied.

[27] If non-EU countries apply the EU ETS carbon price on EU exports (retaliation), the effect on EU production would be relatively small as the EU industries already produce goods with low energy and carbon contents and any retaliatory carbon pricing has limited impacts on their production costs and selling prices.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

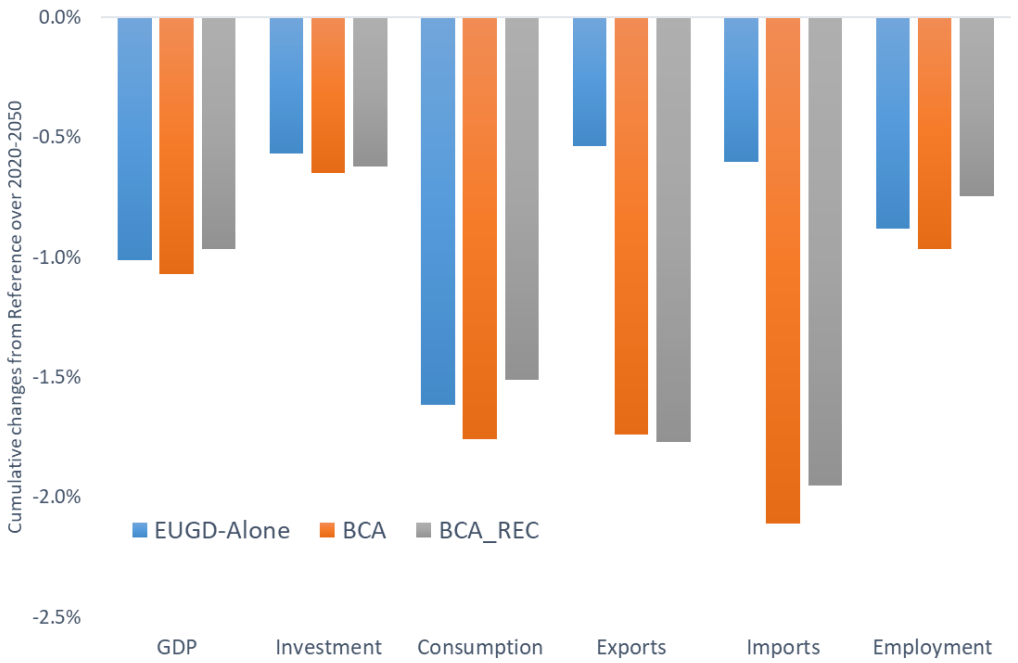


Figure 31: Macro-economic impacts of alternative EU Green Deal scenarios relative to Reference (cumulative changes over 2025-2050)

The leakage-reduction effect of BCA is directly reflected in total GHG emissions in abating and non-abating countries, with global cumulative GHG emissions declining by 0.25% from EUGD-Alone scenario over 2025-2050. This means that in the BCAM context, the EU may even scale down its domestic emission requirement and achieve the same climate outcome, e.g. the same global emission budget by 2050. On global cost-effectiveness grounds, BCA helps to re-allocate emissions between the abating and non-abating countries in the cost-saving direction, as global emissions decline from Reference levels, without any impact on global GDP . However, it should be noted that BCA is only second-best instrument as overall emissions in non-abating countries are still above the Reference levels and considerably higher relative to what is required to meet the Paris Agreement temperature goals.

Competitiveness concerns of regulated Energy Intensive Trade Exposed (EITE) industries are central to the debate on unilateral climate policies, especially in the EU. Unilateral emission pricing increases the risks of relocation for EITE industries where energy costs represent a high share in their total production costs, thus putting these industries at a disadvantage relative to international competitors (Bohringer et al, 2012). The EU maintains a competitive position in the global production of energy intensive products, despite losing market share over 2015-2050 in the Reference scenario due to increasing competition from rapidly growing developing economies. The EU-based industrial manufacturing declines in the EUGD_Alone scenario, induced by high carbon pricing, the lower domestic demand and reduced international competitiveness. The EU share in global production of energy intensive products declines by about 0.5 percentage point relative to the Reference scenario. The imposition of BCAM measures minimises the risks of industrial relocation to non-EU countries and thus the European industrial production returns close to their shares in the Reference scenario. Metals, Chemicals and Non-Metallic Minerals have the highest sectoral performance in the BCAM scenario

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

because of their higher carbon intensity and share of EU imports compared to the other sectors of the EU ETS.

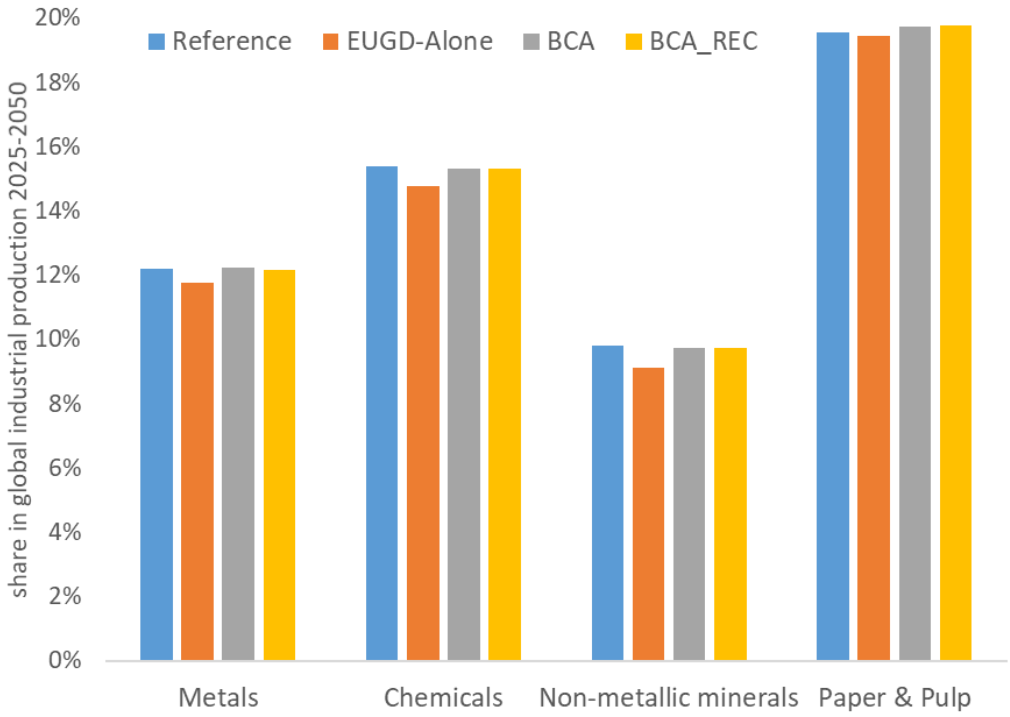


Figure 32: EU share in global industrial production in alternative scenarios (in cumulative terms over 2025-2050)

5.5 Policy Recommendations and Conclusions

Given the lack of globally concerted climate action, the EU already implements ambitious climate policies while the European Green Deal communicated by the EC in December 2019 confirms its commitment to tackling climate and environmental-related challenges. Recently, with the 2030 Climate Target Plan, the EC proposes to raise the EU's ambition on reducing greenhouse gas (GHG) emissions to at least 55% below 1990 levels by 2030 paving the way towards the transition to climate neutrality by mid-century. However, the cost-effectiveness of unilateral climate actions inherently suffers from the lack of "where-flexibility", as unilateral climate policies cannot be imposed to countries without emission regulation in place. In addition, unilateral emission abatement increases the risk of carbon leakage, i.e. the relocation of GHG emissions to countries with weaker or no environmental regulation. Two main channels for carbon leakage are identified: the energy price channel where fossil fuel consumption increases in non-abating countries as international energy prices get depressed from demand reductions in abating regions; and the industrial competitiveness channel, through shifts in comparative advantage of EITE industries which are relocated to non-abating countries. Given that most policy concerns are related to the competitiveness channel with regard to the high cost burden imposed on domestic EITE industries that face increasing relocation risks, our study focuses on this channel and aims to explore potential measures to reduce these negative impacts.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

The enhanced version of the leading multi-sectoral GEM-E3-FIT model is used to explore a series of alternative policy scenarios in order to analyse the macro-economic and trade impacts of asymmetric climate policies and the resulting carbon leakage. The model-based scenarios are policy relevant, as they explore the most recent policy debate and climate pledges, including the EU goal to climate neutrality by 2050, the Chinese pledge for carbon neutrality by 2060 and the introduction of Border Carbon Adjustment as the main policy instrument to minimise carbon leakage and industrial relocation to non-abating countries. In the debate on unilateral climate policy design, BCA has been suggested in the EU Green Deal as a potential instrument to protect domestic industrial activities. As there are inherent difficulties in implementing rebates of emission payments on exports from EU sources, we assume that BCA is implemented through tariffs on embodied emissions of goods imported to the EU from unregulated trading partners, in order to level the playing field between domestic and imported products in the EU with respect to carbon costs.

In case of unilateral EU climate policies aiming to achieve climate neutrality by 2050, there is a positive carbon leakage of 25% because of the redistribution of trade of commodities between the countries as a result of changes in the competitiveness of EU vis-à-vis the non-abating countries. Most of the leakage occurs in China and India that have sufficient production capacities at low cost and relatively high energy and carbon intensities inducing higher increase in emissions, while low transportation costs to the EU market favour Russia and Turkey. The size and the composition of the economies participating in the climate group matters for the leakage rate, as an EU-China coalition leads to a dramatically reduced leakage rate (of about 6% over 2025-2050). A key factor explaining the result is the high effectiveness of the carbon price to reduce emissions in countries, such as China, which have significantly higher energy and carbon intensity and lower industrial production costs compared to the EU and other developed economies.

In absolute terms the increased emissions in non-abating countries are lower than the decreased emissions in abating countries, because of restructuring away from carbon intensive activities induced by high carbon prices in abating countries. By decomposing the leakage by sector of activity, large amounts leaked correspond to additional emissions in power generation of the non-abating countries. This is directly related to the industrial competitiveness channel, as increased industrial activity in non-abating countries requires higher amounts of electricity production, which emit high amounts of GHG emissions given that the power mix in these countries heavily depends on fossil fuels. Measures focusing on reducing emissions in power generation in these countries would greatly help reducing leakages without applying economy wide carbon pricing. Among the energy intensive sectors, metal production and the chemicals sector experience the highest leakage rates, as they are characterized by high energy intensity and high trade exposure. The leakage in building materials sectors is smaller because of lower trade exposure.

In case that EU and China join forces to reduce GHG emissions, the activity impacts are larger in the Chinese economy, as it has higher emissions and carbon intensity than the EU and bears about 85% of the overall mitigation effort. In this context, the cost competitiveness of European industries vis-à-vis the Chinese improves considerably, and thus EU industrial activity losses are very small relative to the Reference scenario. These results indicate that linking the carbon markets of EU and China reduces the international competitiveness of China's energy intensive sectors but increases the competitiveness of EU's sectors. When both China and the EU set more ambitious emission reduction targets

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

for ETS sectors, the adverse impacts of linking on the international competitiveness of China's energy intensive sectors intensify.

The objective of our study is to inform European and international policy makers with respect to the benefits and costs of BCA as a complementary measure to domestic climate policy. In this context, we find that the imposition of BCAM can effectively reduce carbon leakage through trade in emission-intensive and trade-exposed industries, thereby attenuating adverse impacts for these sectors in unilaterally abating countries, i.e. the EU. We also show that the adopted recycling scheme for carbon revenues is highly important, with model-based outcomes suggesting that the use of BCAM revenues to reduce social security contributions is highly beneficial for domestic employment.

The results of our study crucially depend on the assumptions made, especially on the values of specific elasticities. In the GEM-E3-FIT model, heterogeneity of traded goods is captured through the choice of Armington elasticities that determine the ease of substitution between domestically produced and imported goods of the same. The higher the Armington elasticities, the stronger is the carbon leakage through the industrial competitiveness channel as countries can more easily substitute the sources for EITE goods in response to climate policy changes. Supply responses of fossil fuel producers are captured through fossil fuel supply elasticities. The higher these supply elasticities are, the lower is carbon leakage through the fossil fuel channel as the decreased fossil fuel consumption in abating regions produces larger reductions in international energy prices.

The study highlights that while a BCAM can be effective in reducing emission leakage and industrial relocation, careful consideration should be given to its design with particular emphasis on how the revenues are used while ensuring compliance with WTO rules so as to limit retaliation from trading partners. Overall, the BCA seems attractive under global efficiency and domestic political economy considerations, but legal and administrative barriers may substantially constrain the scope for efficiency gains through BCA, while its burden-shifting potential could be perceived as a means for back-door trade policy against developing countries in view of the UNFCCC principle of common but differentiated responsibility and respective capabilities.

References

Fragkos P. (2020), Global Energy System Transformations to 1.5° C: The Impact of Revised Intergovernmental Panel on Climate Change Carbon Budgets, Energy Technology 8 (9), 2000395

DeCian, E,. Parrado, R., Grubb, M., Drummond, P., Coindoz, L., Mathy, S., Stolyarova, E., Georgiev, A., Sniegoki, A., Bukowski, M. (2017), A review of competitiveness, carbon leakage and EU policy options in the post-Paris landscape, Deliverable 3.1 of the COP21-RIPPLES H2020 project.

Kriegler E, Riahi K, Bauer N, V.J. Schwanitz, et al (2015) Making or breaking climate targets: The AMPERE study on staged accession scenarios for climate policy. Technological Forecasting and Social Change, Volume 90, Part A, January 2015, Pages 24–44

Weyant, J.P. (Ed.), 1999. The Costs of the Kyoto Protocol: A Multi-model Evaluation. *The Energy Journal* (Special Issue), 1–390.

Paroussos, P Fragkos, P Capros, K Fragkiadakis, 2015, Assessment of carbon leakage through the industry channel: the EU, perspective Technological Forecasting and Social Change 90, 204-219

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Hoel, M., 1991. Global Environmental Problems: The Effects of Unilateral Actions Taken by One Country. *Journal of Environmental Economics and Management*, 20, 55–70; DOI: 10.1016/0095-0696(91)90023-C

Böhringer, C., Carbone, J., Rutherford, T.F., 2011. Embodied carbon tariffs. NBER working paper, 17376, Cambridge

Cosbey, A. et al., 2012. A Guide for the Concerned: Guidance on the elaboration and implementation of border carbon adjustment. International Institute for Sustainable Development. Draft version 13, August 2012

IEA, World Energy Outlook, 2019, International Energy Agency, Paris

Paroussos et al. (2019): Climate clubs and the macro-economic benefits of international cooperation on climate policy, 2019, Nature Climate Change, Volume 9, Issue 7, 542-546.

Karkatsoulis P, Capros P, Fragkos P, Paroussos L and Tsani S 2016 First-mover advantages of the European Union's climate change mitigation strategy Int. J. Energy Res. 40 814–30

Böhringer C., Balistreri E., Rutherford T. 2012. The role of border carbon adjustment in unilateral climate policy: Overview of an Energy Modeling Forum study (EMF 29), Energy Economics, Volume 34, Supplement 2, December 2012, Pages S97-S110, ISSN 0140-9883

Boeters, S. and J. Bollen, Fossil fuel supply, leakage and the effectiveness of border measures in climate policy. Energy Economics, 2012. 34, Supplement 2(0): p. S181-S189.

Carbone J., Rivers N., 2017, The Impacts of Unilateral Climate Policy on Competitiveness: Evidence from Computable General Equilibrium Models, Review of Environmental Economics and Policy, volume 11, issue 1, Winter 2017, pp. 24–42, doi:10.1093/reep/rew025

Alexeeva-Talebi, V., Christoph Böhringer, Andreas Löschel and Sebastian Voigt, The value added of sectoral disaggregation: Implications on competitive consequences of climate change policies. Energy Economics, 2012. 34, Supplement 2(0): p. S127-S142

Bauer Nico, Valentina Bossetti, et al, 2015, CO2 emission mitigation and fossil fuel markets: Dynamic and international aspects of climate policies. Technological Forecasting and Social Change,

Fragkos P, Tasios N. et al (2017), Energy system impacts and policy implications of the European Intended Nationally Determined Contribution and low-carbon pathway to 2050, Energy Policy, Volume 100, Pages 216-226

Capros P, De Vita A, Tasios N, et al. (2016) EU Reference scenario 2016 – Energy, transport and GHG emissions Trends to 2050. European Commission Directorate General for Energy, Directorate General for Climate Action and Directorate General for Mobility and Transport

Armington Paul S., 1969, A Theory of Demand for Products Distinguished by Place of Production. IMF Staff Papers, 1969. 16(1): p. 159-178.

IRENA (2020), Renewable Power Generation Costs in 2019, International Renewable Energy Agency, Abu Dhabi

Zachmann, G. and McWilliams, B. (2020) 'A European carbon border tax: much pain, little gain', Policy Contribution 05/2020, Bruegel

European Commission, DG ENER(2020), Study on energy prices, costs and their impact on industry and households

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*

Wesseling, J. H., Lechtenböhmer, S., Åhman, M., Nilsson, L. J., Worrell, E., & Coenen, L. (2017). The transition of energy intensive processing industries towards deep decarbonization: Characteristics and implications for future research. *Renewable and Sustainable Energy Reviews*, *79*, 1303–1313.

*"This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No **730403**"*