



Net0 Pathways through improved IAMs across Sectors, dimensions, and scales

Deliverable 3.3: IAMs with improved representation of finance & innovation

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Executive Summary

Implementing the Paris Agreement goals requires rapid and full decarbonization of the economy, involving a fundamental transformation of current economic and societal systems. Integrated Assessment Models (IAMs) have played a critical role in supporting climate policy at national, European, and global levels over the last decade. With the rise of net-zero policy targets, policy packages, and consideration of multiple dimensions and sectors, the role of IAMs has become ever more important with their ability to consider complex inter-relationships between the economy and the environment and to provide robust numerical results. However, existing modelling frameworks need to be enhanced to effectively respond to the new challenges posed by ambitious decarbonization, disruptive events and broad societal trends such as digitalisation and technological change and their links to climate policy.

Technological progress and the availability of low-cost finance to enable the further development and deployment of low-carbon technologies are key factors in paving the way to decarbonization. This is true both for demand-side and supply-side transformations, as technologies enabling the required structural economic changes and promoting sustainable lifestyles must be further developed and financed. To gain a better understanding of these challenges, the PRISMA project developed major advancements in the representation of the financial sector and technological innovation in a series of IAMs, incorporating novel methodologies and integration of state-of-the-art empirical research on (technologically differentiated) cost of capital.

The modelling of the financial sector in IAMs is under-developed and thus IAMs provide little insight on how necessary investments and innovations to enable a low-carbon transition can or should be financed. In order to enhance the financial sector representation in IAMs, we developed three studies presented in this report. First, Section 2 presents a study on the extension of the GEM-E3 Computable General Equilibrium (CGE) model to incorporate a dedicated financial module, enabling a more comprehensive analysis of climate policy impacts and transition risks. Traditional CGE models assume frictionless capital markets and homogeneous investment behaviour, which limits their ability to capture the complex interactions between financial systems and climate mitigation pathways. The extended and enhanced GEM-E3 model can simulate how climate policies influence financial stability, sectoral reallocation of capital, and the emergence of transition risks. It also enables the assessment of climate finance strategies, such as concessional lending and blended finance, and their role in unlocking low-carbon investments, particularly in developing economies. Scenario analysis demonstrates that financial constraints and institutional disparities affect the pace of decarbonization, underscoring the need for integrated policy design. Section 3 presents a study (forthcoming scientific paper) soft-linking the IAM WITCH to a macro-financial agent-based model (the Dystopian Schumpeter Meeting Keynes, DSK). The hybrid framework allows us to translate energy system transitions into macro-financial outcomes at business cycle frequency. The results reveal that rapid transitions induced by fast-growing carbon prices significantly impact unemployment, inflation, and income distribution. Stabilization policies reduce these economic fluctuations, though not completely so in 1.5°C-compatible scenarios. The study emphasizes the need for coordinated climate and macroeconomic policy during decarbonisation and showcases how model integration can lead to a better understanding of the economic and financial implications of low-carbon futures. Finally, section 6 quantifies the impact of differentiated Cost of Capital on global mitigation strategies by incorporating dynamic, region- and sector-specific financing conditions into the IMAGE IAM, covering nine energy and industry sectors beyond electricity generation. The study results shows that accounting for heterogeneous financing conditions increases cumulative global mitigation costs, shifting investment away from capital-intensive options such as renewables, grids and electrolysis-based hydrogen especially in developing countries.

While low-carbon technologies play a key role in stabilising the climate, technological progress is often not endogenized in IAMs, and when it is it lacks a strong empirical basis. PRISMA aims to strengthen the modelling of endogenous technological change in IAMs, and several studies included in this report present the enhanced representation of low-carbon innovation in models. In particular, section 4 describes the interplay between

green innovation and low-carbon taxes in a DSGE model enhanced with endogenous innovation dynamics. The study highlights a strong complementarity between rising carbon taxes and front loaded, time limited R&D support: when firms internalize an anticipated path of higher CO₂ prices, they invest heavily in green knowledge early on, and when those efforts are co-financed from carbon tax revenues, diffusion and adoption accelerate, allowing a given climate target to be achieved at lower tax levels or, for a given tax, with faster emissions reductions. Section 5 presents the technological change advancements in the WITCH model, in particular the introduction of digital services and technologies. A dedicated digitalisation sector is introduced in the model that reflects both the productivity-enhancing effects of digital services and their dependence on electricity use. This allows for a more nuanced analysis of the interactions between digitalisation and energy systems transition. Digital technologies affect energy systems along two dimensions. First, the operation of these technologies directly consumes electricity, while digitalisation can also contribute to energy efficiency improvements, such as through smart grids, building automation systems, or AI-assisted optimisation in manufacturing. The study shows that digitisation influences both total energy consumption and the fuel mix use, with positive impacts for electrification.

Section 7 presents an exploratory study on introducing technology-specific spillovers in the IMAGE model. Spillovers describe how the deployment of a technology in one region influences its deployment in other regions. This study investigates how modifying the structure of knowledge flows and spillovers affects clean technology adoption and global emissions trajectories. The study shows that the assumption about cross-regional spillovers can have a substantial effect on the cost of solar PV with international spillovers accelerating the cost reduction of low-carbon technologies. Section 8 presents an open-source Python-based tool to exogenously project investment and fixed operational & maintenance costs of energy technologies with regional specificity across scenarios. The tool offers a standardized, modular approach that simplifies the input process and promotes the reproducibility of cost projections within models, providing a valuable resource for more transparent model design. The application of the tool is demonstrated within the MESSAGEix model by projecting costs for energy technologies until 2100; however the tool can also be adapted for use in other models, as well as applications for technologies in non-energy sectors such as the steel or chemical industry. Finally, section 9 presents a study that examines the impact of barriers to knowledge diffusion in energy technologies in 29 countries from 1990 to 2015, distinguishing between efficient fossil-based generation and mature renewable options, namely wind and solar. The study shows that knowledge flows are higher in countries with similar technological profiles, particularly for mature renewables, and finds that international knowledge spillovers have increased in intensity for wind and solar PV, while the opposite is true for fossil-based technologies. This indicates that foreign knowledge has increasingly informed domestic investors and points to the key role that knowledge flows from abroad had in promoting innovation in low-carbon technology options.

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1 Introduction

Technological progress and the availability of low-cost finance to enable the further development and deployment of low-carbon technologies are key factors in paving the way to decarbonization. This is true both for demand-side and supply-side transformations, as technologies enabling sustainable lifestyles and the necessary structural changes in national economies must be further developed and financed. To gain a better understanding of these challenges, the PRISMA project developed major advancements in the representation of the financial sector and technological innovation in a series of Integrated Assessment Models (IAMs), incorporating novel methodologies and integration of state-of-the-art empirical research on (regionally and technologically differentiated) cost of capital.

The modelling of the financial sector in IAMs is under-developed and thus IAMs provide little insight on how necessary investments and innovations to enable a low-carbon transition can or should be financed. In order to enhance the financial sector representation in IAMs, we used alternative methodologies (agent-based models, macro-financial/flow-of-funds models, stock-flow models, empirical work on the cost of capital for different technologies) to enhance the integration of the financial sector in the macroeconomic model GEM-E3 (Section 2) and in the IAM WITCH (Section 3), while Section 6 presents how the differentiated cost of capital has been integrated into the IMAGE model.

While low-carbon technologies play a key role in stabilising the climate, technological progress is often not endogenized in IAMs, and when it is it lacks a strong empirical basis. The task 3.4 of the PRISMA project is dedicated to strengthening the modelling of endogenous technological change in IAMs and several studies are included in this deliverable aiming to enhance the representation of innovation in models: Section 4 discusses the role of Innovation and carbon taxes nexus in the DSGE model (enhanced with endogenous innovation dynamics), while Section 5 presents the technological change advancements in the WITCH model, in particular the introduction of digital services and technologies in the model code. Section 7 presents an exploratory study on introducing technology-specific spillovers in the IMAGE model, Section 8 presents a tool to simulate the future development of technology costs under different development scenarios and Section 9 presents a study aiming to quantify the international knowledge spillovers in energy technologies.

2 Extending GEM-E3: Integrating Financial Sector Dynamics into a CGE Framework for Climate Policy Analysis

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This study presents an extension of the GEM-E3 Computable General Equilibrium (CGE) model to incorporate a dedicated financial module, enabling a more comprehensive analysis of climate policy impacts and transition risks. Traditional CGE models, including GEM-E3, often assume frictionless capital markets and homogeneous investment behaviour, which limits their ability to capture the complex interactions between financial systems and climate mitigation pathways.

The extended GEM-E3 model can be used to simulate how climate policies influence financial stability, sectoral reallocation of capital, and the emergence of transition risks, including systemic vulnerabilities. It also enables the assessment of climate finance strategies, such as concessional lending and blended finance, and their role in unlocking low-carbon investments, particularly in developing economies. Scenario analysis demonstrates that financial constraints and institutional disparities significantly affect the pace and distribution of decarbonization, underscoring the need for integrated policy design.

This work contributes to the growing literature on financially-aware IAMs and CGE models, offering a robust tool for policymakers, financial institutions, and researchers to evaluate the economic and financial implications of climate action under uncertainty.

2.1 Introduction

Climate change presents profound challenges to economic systems, requiring robust analytical tools to evaluate the implications of policy interventions. Computable General Equilibrium (CGE) models have long served as a cornerstone for assessing the economy-wide impacts of climate policies, offering a comprehensive representation of intersectoral linkages, resource allocation, and welfare effects. However, traditional CGE frameworks often abstract away from the complexities of financial markets, limiting their ability to capture the full spectrum of macroeconomic feedbacks and risks associated with climate transitions.

In recent years, the financial sector has emerged as a critical actor in the climate policy landscape. Investment flows, credit allocation, asset revaluation, and risk pricing are increasingly influenced by climate-related factors, including regulatory shifts, technological change, and physical climate risks. Integrating financial sector dynamics into CGE models is therefore essential to enhance the realism and policy relevance of climate-economic assessments. Such integration allows for a more nuanced understanding of how financial constraints, investor behavior, and monetary policy interact with climate mitigation strategies, potentially amplifying or dampening their economic effects.

This work proposes a novel extension of the CGE framework that incorporates key financial sector mechanisms, including capital market responses, and financial risk transmission. By embedding these dynamics into a climate policy modeling context, we aim to provide a more holistic tool for evaluating the trade-offs and synergies between environmental goals and financial stability. The enhanced model is applied to a set of climate policy scenarios to illustrate how financial frictions can shape the outcomes of the additional investment requirements that are necessary on the transformation of the economic system in climate policy scenarios.

2.2 Methodological Approach

This study enhances the GEM-E3 model—a multi-regional, multi-sectoral Computable General Equilibrium (CGE) framework—by integrating financial sector dynamics to better capture the macroeconomic implications of climate policy. The extension is implemented in four sequential steps, each building upon the standard version of GEM-E3, which traditionally abstracts from detailed financial market interactions.

Step 1: Extension of the Accounting Framework to Include Financial Assets and Liabilities

In the standard GEM-E3 model, agents are characterized by their production, consumption, and trade behavior, but financial positions are not explicitly modeled. The first step introduces a financial accounting layer:

- Households, firms, and government agents are endowed with balance sheets that include financial assets (e.g., deposits, government bonds, corporate bonds) and liabilities (e.g., loans, debt securities).

The rest of the world is modeled through external financial positions, enabling the tracking of capital flows and foreign debt. These financial stocks evolve over time based on savings, investment, and borrowing decisions, and are linked to the Social Accounting Matrix (SAM) structure.

This extension allows the model to track intertemporal financial linkages and lays the foundation for modeling interest flows and financial constraints.

Step 2: Introduction of Interest Rates and Financial Income Flows

The second step introduces an interest rate that governs the returns on assets and the cost of liabilities:

- Interest income from assets is added to household and firm income, affecting consumption and investment decisions.
- Interest payments on liabilities are treated as expenditures, reducing disposable income and firm profitability.
- Interest rates can be differentiated by asset class and agent type, and may be exogenous or endogenously determined via monetary policy rules or financial market clearing conditions.

This step enables the model to capture the transmission of monetary policy and the income effects of financial positions.

Step 3: Modeling Financial Behavior

In the third step, behavioral rules are introduced to private and public debt repayment and accumulation:

- Agents allocate a portion of their income to keep the debt constant.
- Debt accumulation is modeled through intertemporal budget constraints, with borrowing decisions influenced by expected future income, interest rates, and policy signals.
- Optional extensions include default risk, credit rationing, or prudential regulation, which can be used to simulate financial stress scenarios or transition risks.

This step introduces financial frictions and allows the model to simulate the impact of climate policies on financial stability and leverage.

Step 4: Endogenizing Investment and Consumption via Financial Mechanisms

The final step links financial conditions to real economic decisions:

- Investment behavior is modeled as a function of expected returns, cost of capital, and access to finance. Climate policies (e.g., carbon pricing, green subsidies) influence these variables through risk-adjusted profitability.
- Consumption decisions are affected by disposable income, wealth effects and credit constraints.
- Financial accelerator mechanisms are introduced, where changes in financial conditions (e.g., asset prices, interest rates) amplify macroeconomic responses.

This step enables the GEM-E3 model to capture feedback loops between climate policy, financial markets, and real economic activity, improving its capacity to assess transition risks, stranded assets, and policy effectiveness

2.2.1 Extension of the Accounting Framework to Include Financial Assets and Liabilities

We consider the following financial instruments and general assumptions regarding financial assets and liabilities:

- **Financial instruments:** Time Deposits, Government Bonds and Corporate Bonds
- **Households:**
 - **Deficit:** Increase Liabilities on Time Deposits
 - **Surplus:** Distributed to financial instruments based on the global share of each instrument to total.
- **Firms:**
 - **Deficit:** Increase Liabilities on Corporate Bonds
 - **Surplus:** Distributed to financial instruments based on the global share of each instrument to total.
- **Government:**
 - **Deficit:** Increase Liabilities on Government Bonds
 - **Surplus:** Distributed to financial instruments based on the global share of each instrument to total.

The new financial assets that are available in the financial market are determined by the new financial liabilities (loans, debt securities etc.). Based on the above assumptions the new financial liabilities are directly linked to time deposits, corporate bonds and government bonds (without assuming a bank intermediary). New liabilities are issued by households, firms and government to serve their deficit.

Each economic agent with financial surplus distribute their income to time deposits, corporate bonds and government bonds based on the global liabilities by agent:

$$New\ Assets_{fi,se,r} = \frac{\sum_r New\ Liabilities_{fi,se,r}}{\sum_{r,fi} New\ Liabilities_{fi,se,r}} \cdot Surplus_{se,r}$$

where **fi** the financial instruments, **se** the economic agents and **r** the regions.

Stock of assets and stock of liabilities follow the stock-flow motion equation:

$$S_t = S_{t-1} + F_t$$

Where: S_t the stock at time t, S_{t-1} the stock at time t-1 and F_t the flow at time t.

The dynamic feedback loop is:

- Real economy generates surplus/deficit
- Surplus/deficit updates financial stocks
- Financial stocks generate income effects
- Income effects influence future real decisions

2.2.2 Introduction of Interest Rates and Financial Income Flows

We consider an exogenous interest rate (for the entire model) that is included as expenditure in borrowers and as income to lenders. The additional income is directed either to consumption or to savings to finance investments. The interest payments from borrowers to lenders are included in flows which leads to higher deficits to the borrowers and higher surpluses to the lenders as compared to the previous case.

2.2.3 Modelling Financial Behaviour

In the extended GEM-E3 framework, financial behavior is modeled to reflect how agents manage their liabilities over time, particularly in response to climate policy shocks and macroeconomic conditions. This includes explicit modeling of debt repayment decisions and mechanisms that ensure debt sustainability.

Economic Agents accumulate and repay debt based on their budget constraints and economic expectations. The evolution of debt is governed by the following stock-flow equation:

$$S_t = S_{t-1} + F_t + R_t$$

where: S_t the stock at time t, S_{t-1} the stock at time t-1, F_t the flow at time t, and R_t the repayments at time t.

Repayment decisions can be designed exogenously or to follow a debt sustainability rule to ensure that debt remains sustainable over the simulation horizon. To this end, the model can incorporate several key assumptions and mechanisms:

- **Intertemporal Budget Constraint:** Agents are subject to a solvency condition that prevents indefinite accumulation of debt. Over time, the present value of future surpluses must cover outstanding liabilities.
- **Interest Rate Feedback:** Interest rates respond to macroeconomic conditions and debt levels. Higher debt may lead to increased borrowing costs, discouraging excessive leverage.

- **Repayment Rules:** Minimum repayment ratios are imposed, ensuring that a portion of income is consistently allocated to debt servicing. These rules can be agent-specific and policy-sensitive.
- **Borrowing Limits:** Agents face endogenous borrowing constraints based on income, collateral, and macro-financial stability indicators. This prevents unsustainable debt expansion, especially under adverse climate transition scenarios.
- **Policy Anchors:** For the government sector, fiscal rules (e.g., debt-to-GDP targets or primary balance conditions) are introduced to guide long-term debt sustainability. These can be adjusted to reflect climate investment needs and green fiscal strategies.

2.2.4 Endogenizing via financial mechanisms

In the extended GEM-E3 framework, endogenous mechanisms are introduced in the model that collect the income required to debt servicing:

- Households adjust consumption and savings based on expected future income and debt obligations.
- Firms optimize capital structure, balancing investment with debt servicing to maintain profitability and creditworthiness.
- Government calibrates public spending and taxation to meet fiscal targets while supporting climate policy objectives.

These dynamics create feedback loops between financial conditions and real economic activity, which are crucial for assessing the macroeconomic impacts of climate policies, especially under scenarios involving large-scale green investment or carbon taxation.

2.3 Data for the financial accounts

The construction of the financial accounting matrix for the GEM-E3 model is a demanding task given the model's extensive regional resolution. For this reason, we have combined data from Eurostat (for EU27 countries), IMF, OECD and UN for extra-EU countries.

The financial accounting framework developed for the GEM-E3 model extension is based on a wide range of macroeconomic and financial datasets sourced from national and international institutions. These datasets are essential for constructing the Financial Social Accounting Matrix (FSAM), monitoring financial flows and stocks, and calibrating the financial sector mechanisms of the model. Data have been collected from multiple sources and, where necessary, combined to ensure consistency and enable validation across agents and regions. The collected datasets include both raw and processed data, organized by institution and tailored for model integration.

The OECD provides annual financial accounts and balance sheets, which include sectoral breakdowns of assets and liabilities as well as financial flows. These data are consistent with the international standards of the System of National Accounts and are used to capture household financial positions, disposable income, and inter-sectoral lending and borrowing.

From the IMF, several datasets have been utilized. These include government balance sheets, financial transactions by institutional sector, and historical data on public and private debt. Together, they offer a detailed view of fiscal positions and financial interlinkages across countries and sectors.

The United Nations National Accounts Statistics offer extensive coverage of sectoral financial accounts for over 200 countries. These data are particularly valuable for non-EU countries and are aligned with the forthcoming System of National Accounts 2025. Sectoral datasets used in this study

include the total economy, rest of the world, non-financial and financial corporations, general government, and households including non-profit institutions serving households. All data are used at current prices.

The World Bank's World Development Indicators provide complementary macroeconomic data that support cross-validation and consistency checks. For EU27 countries, Eurostat data are used to assess net lending and borrowing positions and to evaluate household financial strength.

The conceptual foundation for harmonizing and integrating these datasets is the System of National Accounts 2025, jointly developed by the EU, IMF, OECD, UN, and World Bank. This framework provides a consistent structure for sectoral financial accounts and supports the integration of financial instruments into the GEM-E3 model.

Although the majority of the required data have already been collected and organized, full integration into the FSAM and the SNA-based financial accounting tool is still in progress. The structure and metadata provided by the SNA 2025 framework offer a clear pathway for harmonization, but additional processing is required to fully reproduce the financial account structure and ensure coherence across agents and regions.

IMF data provides the stock of public and private debt in 2024, Table 1. New liabilities by agent determine the accumulation of debt in the period 2025 – 2050.

Table 1: Public and private debt in 2024, as a % of GDP

	Households	Firms	Private	Public
EU27	51%	102%	153%	85%
GBR	76%	61%	137%	101%
USA	69%	74%	143%	121%
JPN	65%	116%	181%	237%
CAN	100%	118%	218%	111%
BRA	36%	57%	93%	87%
CHN	61%	144%	206%	88%
IND	41%	50%	91%	81%
KOR	90%	111%	201%	52%
IDN	16%	22%	38%	40%
MEX	16%	21%	37%	40%
ARG	5%	19%	23%	85%
TUR	11%	47%	57%	29%
SAR	35%	46%	81%	30%
OCE	112%	61%	173%	50%
RUS	22%	77%	99%	20%
ARE	25%	76%	101%	32%
REP	60%	94%	154%	98%
SAF	34%	33%	67%	76%
REU	89%	144%	233%	43%
ROW	60%	94%	154%	98%
WORLD	60%	94%	154%	98%

* IMF: Global Debt Database

2.4 Policy Scenarios

A real policy scenario and a variant scenario are considered to compare the model results computed by adopting the above steps. The aim is to help the reader understand and assess how

results from the policy scenarios in the main body of this report compare to these two cases, particularly with regards to the level of impact of the energy transition.

The **core policy scenario** (CPS) reflects established and incoming policies, particularly the Fit for 55 (FF-55) package for EU27 Member States aiming at a 55% reduction in net GHG emissions (compared to 1990 levels) by 2030, as well as the policy objectives of 90% net reduction by 2040 and net-zero by 2050. In this scenario the model determines key economic outcomes such as GDP and sectoral output, endogenously based on policy assumptions. Recently adopted policy mechanisms under the Fit for 55 package, such as ETS2, CBAM, CO2 standards for vehicles and shipping decarbonisation are included in this scenario. As far as the post-2030 period is concerned, the overall mitigation targets (net 90% in 2040 and net zero in 2050) are achieved mainly via carbon pricing in ETS1 and ETS2 sectors, but without embedding any explicit assumptions about what the post-2030 framework will look like.

ETS2 is introduced from 2027 covering direct fuel use in buildings, road transport, and small industries not covered under ETS1. The carbon price in this case starts at an initial 45€ (in 2020 prices), converging to the price of ETS1 by 2050. The scope of ETS1 is also expanded post 2023 revision, including maritime transport, setting as an emission reduction target of 62% by 2030 with respect to 2005 levels, and phasing-out free allowances.

CBAM is linearly introduced under the core policy scenario from 2026 (fully implemented by 2035), covering iron, steel, cement, fertilizer, aluminium, hydrogen and electricity markets. We also explicitly model CO2 standards by introducing a ban on the sale of new ICE vehicles from 2035. Shipping decarbonisation is also considered by explicitly reducing GHG emission intensity of energy usage on-board ships by up to 80% by 2050. Other policy assumptions such as from the renewable energy and energy efficiency directives are also considered.

The recycling of extra revenues depends on the specific climate policy. For the revised ETS1 and CBAM policies, 100% of revenues are re-distributed for climate-related purposes. For the incoming ETS2 only 62.5% is re-distributed for climate-related purposes, with the remaining 37.5% being paid as lump-sum transfers to vulnerable households.

The debt-to-GDP ratio cannot increase over time compared to 2023 values. This implies a balancing instrument adjustment factor via general taxation to maintain this balance in the case of excess revenues or expenditures.

Table 2 below summarizes key assumptions used in the core policy scenario to derive the results.

Table 2 Key Assumptions adopted in the Core Policy Scenario

Key Assumption	Core Policy Scenario
Socio-economic	
GDP & Population	Exogenously determined based on 2024 Ageing Report ¹ growth rate trends for EU27 by member state and on IMF-WB ² & SSP2-OECD ENV-Growth 2023 ³ rates for non-EU countries / regions.
Mitigation Policies	
Included Policies	ETS1 post-2023 revision, ETS2, CBAM, CO2 emission standards for cars, Shipping decarbonization, energy efficiency & renewable energy directives, social climate fund, energy taxes.
Carbon Price	Endogenously determined in line with emission targets.
Revenue Recycling	100% of revenues from ETS1 & CBAM re-invested for climate related purposes. 62.5% of revenues from ETS2 re-invested for climate related purposes. 37.5% as lump-sum transfers to vulnerable households.

¹ [2024 Ageing Report. Underlying Assumptions and Projection Methodologies - European Commission](#)

² [World Economic Outlook Database, October 2023](#)

³ <https://data.ece.iiasa.ac.at/ssp>

Rest of World (non-EU) Mitigation Efforts	Achieve Nationally Determined Contributions (NDCs) for 2030 and continuation of such policies for 2050, following stylized, economy-wide carbon-pricing implementation.
Energy System & Emissions	
Energy Demand	Endogenously determined based on optimisation of resources and socio-economic assumptions.
Global Fossil Fuel Commodity Prices	Exogenously set based on REF 2025 projections.
Fossil Fuel Taxes & Subsidies	Energy taxes and subsidies have been calibrated to historical data available in 2021. 50% phase-out of subsidies by 2030, 100% phase out by 2035, compared to 2021 levels.
Emissions	In line with Fit-for-55 (net 55% GHG emissions reduction by 2030 compared to 1990 levels), net 90% reduction by 2040, and net-zero by 2050.

A variant of the core policy scenario is used for comparison purposes. An exogenous increase of firms investment is introduced to illustrate the key financial mechanisms of the model.

2.5 Core Policy Scenario Results

In this scenario several high-level socio-economic trends are taken as given, hence the results in some cases reflect projections and trends taken from existing study. Key results are presented in the following subsections.

2.5.1 Impacts on GDP

The annual GDP growth rates by country is presented in Table 3. Emerging countries like India, Turkey and Indonesia have an average annual growth rate for the period 2025 – 2050 above 3%. Developed countries like EU27, Japan and USA have an average annual growth rate below 2%. At the world level the average annual growth rate in the period 2025 -2050 is: 2.4%.

Table 3: Annual growth rate of GDP – CPS scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
EU27	1.7%	1.8%	1.7%	1.5%	1.3%	1.3%	1.2%	1.6%	1.8%	1.7%
GBR	1.8%	2.1%	2.2%	2.1%	1.8%	1.9%	2.0%	2.1%	2.1%	1.9%
USA	1.9%	2.3%	2.4%	2.4%	2.3%	2.4%	1.7%	1.6%	1.4%	1.4%
JPN	1.0%	0.9%	0.9%	0.9%	0.7%	0.9%	1.1%	1.1%	1.1%	1.1%
CAN	2.9%	2.2%	2.2%	2.2%	1.7%	1.6%	2.4%	2.4%	2.3%	2.1%
BRA	1.8%	2.2%	2.5%	2.5%	2.5%	2.5%	3.0%	3.5%	3.6%	3.6%
CHN	4.7%	4.8%	4.3%	3.9%	3.7%	3.9%	3.2%	2.4%	2.1%	2.0%
IND	6.9%	6.9%	7.4%	7.3%	6.4%	6.5%	5.1%	4.5%	4.1%	3.8%
KOR	2.8%	2.9%	2.9%	2.9%	2.9%	2.9%	1.8%	1.5%	1.2%	1.0%
IDN	5.1%	5.2%	5.0%	5.0%	4.8%	4.7%	3.5%	3.2%	2.8%	2.5%
MEX	1.1%	2.1%	2.4%	2.5%	2.3%	2.3%	3.1%	3.0%	2.9%	2.8%
ARG	3.2%	3.0%	2.8%	2.5%	2.6%	2.6%	2.2%	2.4%	2.5%	2.6%
TUR	5.8%	5.1%	4.3%	4.1%	4.1%	4.1%	4.0%	3.1%	2.5%	2.1%
SAR	2.4%	2.9%	2.7%	2.4%	2.6%	2.8%	2.8%	2.3%	2.0%	1.9%
OCE	2.1%	1.9%	2.1%	2.1%	2.1%	2.1%	2.6%	2.6%	2.4%	2.4%
RUS	0.6%	1.2%	1.0%	1.0%	1.2%	0.8%	2.1%	1.9%	1.9%	1.8%
ARE	3.8%	4.7%	4.5%	4.6%	4.5%	4.5%	4.3%	3.7%	3.2%	2.8%
REP	2.3%	2.4%	2.2%	2.1%	2.2%	2.1%	2.8%	3.1%	3.0%	3.1%
SAF	1.0%	1.3%	1.1%	1.6%	1.2%	1.1%	2.7%	3.3%	3.5%	3.5%

REU	2.1%	2.4%	2.0%	2.1%	2.1%	2.1%	2.4%	2.2%	2.0%	1.9%
ROW	3.8%	3.8%	3.9%	3.9%	4.0%	4.0%	4.0%	3.6%	3.4%	3.3%
WORLD	2.8%	3.0%	3.0%	2.9%	2.7%	2.8%	2.5%	2.4%	2.3%	2.2%

Source: GEM-E3

2.5.2 Impacts on Investment

Investments as % of GDP are presented in Table 4. Emerging countries like India, China, Indonesia have a higher share as compared to Emerged economies (i.e. EU27, USA).

Table 4: Investments (% of GDP) – CPS scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
EU27	22.1%	22.6%	22.6%	22.7%	22.7%	22.6%	22.5%	22.1%	21.7%	21.2%
GBR	17.7%	17.6%	17.6%	17.6%	17.7%	17.5%	17.2%	17.1%	17.0%	16.9%
USA	20.9%	21.0%	21.2%	21.2%	21.2%	21.2%	21.0%	20.7%	20.6%	20.4%
JPN	25.7%	25.6%	25.5%	25.3%	25.3%	25.2%	24.9%	24.7%	24.4%	24.1%
CAN	22.2%	22.3%	22.2%	22.2%	22.2%	22.1%	21.9%	21.5%	21.3%	21.2%
BRA	16.9%	16.8%	16.6%	16.5%	16.5%	16.4%	16.2%	15.9%	15.7%	15.4%
CHN	38.9%	38.7%	38.5%	38.3%	38.1%	37.9%	37.0%	36.2%	35.4%	34.6%
IND	33.8%	33.8%	33.7%	33.6%	33.6%	33.3%	32.6%	32.0%	31.5%	31.0%
KOR	28.2%	28.0%	28.1%	27.8%	27.3%	27.3%	26.8%	26.4%	26.1%	25.9%
IDN	31.9%	31.8%	31.8%	31.8%	31.6%	31.5%	30.9%	30.4%	29.8%	29.3%
MEX	20.0%	19.9%	19.9%	19.8%	19.8%	19.8%	19.6%	19.4%	19.1%	18.9%
ARG	20.3%	21.1%	21.7%	22.5%	22.4%	22.4%	22.1%	21.8%	21.4%	21.1%
TUR	13.2%	11.9%	11.0%	10.5%	10.5%	10.5%	10.3%	10.2%	10.2%	10.1%
SAR	29.7%	30.2%	31.2%	31.1%	30.9%	30.6%	29.7%	28.6%	28.0%	27.5%
OCE	25.4%	25.7%	25.6%	25.7%	25.6%	25.4%	25.0%	24.4%	24.1%	23.8%
RUS	24.1%	24.1%	24.3%	24.3%	24.3%	24.4%	24.2%	23.8%	23.3%	22.9%
ARE	29.2%	28.7%	28.3%	28.0%	27.7%	27.2%	26.4%	25.9%	25.5%	25.0%
REP	28.7%	28.7%	28.6%	28.5%	28.4%	28.3%	28.0%	27.2%	26.6%	26.0%
SAF	16.2%	16.6%	16.5%	17.0%	17.0%	17.1%	16.8%	16.5%	16.3%	16.0%
REU	26.3%	26.6%	26.9%	27.1%	27.1%	27.0%	26.9%	26.4%	26.0%	25.6%
ROW	22.7%	22.5%	22.4%	22.3%	22.2%	22.4%	20.8%	19.8%	19.2%	18.7%
WORLD	25.9%	26.0%	26.1%	26.1%	26.0%	26.1%	25.6%	25.2%	24.7%	24.3%

Source: GEM-E3

2.5.3 Savings

The GDP trajectory is produced by changing several parameters in the model (i.e., population growth, productivities, behavior parameter) that affect the productive capacity of each economy and its' competitiveness. Exogenous assumption on the components of GDP (household consumption, investment, government expenditures) are imposed that affect the savings rates and the level of investment. Economies with low savings rates and high investments tends to be net borrowers. This has no cost in borrowers if the financial accounts and the debt accumulation are not considered.

Table 5 presents the savings by country for the period 2025 – 2050. In the standard version of the GEM-E3 model the total savings are collected to total investments, Table 4.

Table 5: Savings (% of GDP) – CPS scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
EU27	26.2%	26.4%	26.2%	26.2%	26.1%	26.0%	25.6%	24.7%	23.9%	23.1%

GBR	15.8%	15.8%	15.8%	15.8%	15.8%	15.6%	15.3%	15.4%	15.4%	15.5%
USA	16.7%	16.9%	17.1%	17.2%	17.2%	17.4%	17.4%	17.4%	17.5%	17.6%
JPN	26.1%	26.0%	25.8%	25.6%	25.6%	25.6%	25.3%	24.9%	24.7%	24.4%
CAN	18.8%	18.6%	18.3%	17.9%	17.9%	17.8%	17.6%	17.4%	17.3%	17.2%
BRA	19.8%	20.1%	20.1%	20.0%	20.0%	20.0%	19.6%	19.0%	18.5%	17.9%
CHN	41.9%	41.5%	41.2%	40.9%	40.6%	40.4%	39.3%	38.2%	37.4%	36.4%
IND	28.6%	28.4%	28.1%	27.7%	27.6%	27.4%	26.9%	26.4%	26.0%	25.6%
KOR	34.4%	34.2%	34.1%	33.9%	33.7%	33.7%	32.9%	32.2%	31.7%	31.2%
IDN	34.7%	34.4%	34.3%	34.1%	33.9%	33.6%	32.9%	32.2%	31.6%	31.1%
MEX	15.9%	16.1%	16.1%	16.1%	16.2%	16.1%	16.0%	15.7%	15.5%	15.2%
ARG	20.5%	21.8%	22.6%	23.5%	23.5%	23.5%	23.4%	23.2%	22.9%	22.6%
TUR	18.4%	20.0%	19.6%	19.5%	19.6%	19.7%	20.5%	21.0%	21.4%	21.7%
SAR	32.7%	33.9%	34.8%	35.5%	35.6%	35.6%	35.0%	33.8%	33.3%	33.3%
OCE	25.2%	25.3%	25.3%	25.3%	25.1%	25.0%	24.5%	24.4%	24.0%	23.7%
RUS	27.7%	28.2%	28.6%	29.0%	29.1%	29.2%	28.5%	28.2%	27.8%	27.6%
ARE	34.1%	34.1%	33.9%	33.6%	33.3%	32.9%	32.0%	30.9%	30.3%	30.0%
REP	37.1%	37.4%	37.9%	38.3%	38.3%	38.2%	37.7%	37.7%	37.4%	37.3%
SAF	16.1%	16.6%	16.9%	17.2%	17.2%	17.1%	16.6%	16.0%	15.5%	14.9%
REU	32.1%	32.1%	32.0%	32.1%	31.9%	31.7%	30.9%	30.2%	29.6%	29.1%
ROW	17.2%	17.5%	17.9%	18.1%	18.2%	18.5%	17.7%	17.2%	17.0%	16.9%
WORLD	25.9%	26.0%	26.1%	26.1%	26.0%	26.1%	25.6%	25.2%	24.7%	24.3%

Source: GEM-E3

2.5.4 Surplus or Deficit by agent

Agent on surplus lends the agents with deficits. As a result (Table 6), there are countries that they are net lenders or borrowers. On the absence of modelling the financial accounts, there is no benefit or penalty depending on the agents' financial position in future income (i.e., interest payments, payback income etc.).

Table 6: Deficit or Surplus of economic agents by region (% of GDP) – CPS scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
EU27	4.3%	4.2%	4.2%	3.7%	3.6%	3.5%	3.5%	3.4%	3.2%	2.7%
GBR	-1.9%	-2.0%	-1.9%	-1.8%	-1.8%	-1.8%	-1.9%	-1.9%	-1.9%	-1.8%
USA	-4.2%	-4.3%	-4.2%	-4.1%	-4.1%	-4.0%	-3.9%	-3.8%	-3.6%	-3.3%
JPN	0.4%	0.6%	0.4%	0.4%	0.4%	0.3%	0.3%	0.3%	0.4%	0.3%
CAN	-2.5%	-3.0%	-3.4%	-3.7%	-3.9%	-4.3%	-4.3%	-4.4%	-4.3%	-4.1%
BRA	1.9%	2.7%	2.9%	3.3%	3.4%	3.5%	3.6%	3.5%	3.4%	3.1%
CHN	3.7%	3.3%	3.0%	2.8%	2.7%	2.6%	2.5%	2.4%	2.2%	2.0%
IND	-4.5%	-4.9%	-5.2%	-5.4%	-5.6%	-5.9%	-6.0%	-5.9%	-5.7%	-5.6%
KOR	6.2%	6.3%	6.3%	6.2%	6.1%	6.1%	6.4%	6.4%	6.1%	5.8%
IDN	3.5%	3.2%	2.8%	2.6%	2.5%	2.3%	2.3%	2.1%	1.9%	1.9%
MEX	-5.1%	-4.1%	-4.1%	-3.8%	-3.7%	-3.7%	-3.6%	-3.7%	-3.5%	-3.7%
ARG	-2.0%	0.3%	0.3%	0.8%	0.9%	1.0%	1.1%	1.1%	1.3%	1.4%
TUR	-6.0%	0.0%	5.2%	8.1%	8.6%	9.0%	9.2%	9.2%	10.2%	10.7%
SAR	2.4%	3.3%	2.9%	3.6%	3.7%	4.4%	4.7%	5.0%	5.3%	5.1%
OCE	0.0%	-0.4%	-0.2%	-0.4%	-0.4%	-0.5%	-0.5%	-0.5%	-0.5%	-0.1%

RUS	3.3%	3.4%	3.6%	4.1%	4.3%	4.7%	4.8%	4.8%	4.3%	4.4%
ARE	5.6%	5.7%	4.9%	5.4%	5.6%	5.6%	5.6%	5.7%	5.7%	5.0%
REP	9.0%	8.1%	8.4%	8.8%	9.3%	9.7%	9.9%	9.8%	9.7%	10.6%
SAF	-0.2%	-0.4%	-0.1%	-0.1%	0.4%	0.2%	0.2%	0.0%	-0.2%	-0.6%
REU	6.8%	6.4%	5.8%	5.5%	5.0%	5.0%	4.9%	4.7%	4.0%	3.8%
ROW	-5.7%	-5.6%	-5.4%	-5.0%	-4.6%	-4.2%	-4.0%	-3.9%	-3.2%	-2.6%
WORLD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Source: GEM-E3

2.5.5 Financial accounts

By adding the financial instruments, we get a better understanding of the financial transactions among economies which can help to improve the dynamics of the macroeconomic projections assumed by linking the financial position with future income. Higher income from assets can assist a higher share of consumption expenditures and lower savings rates as compared with the countries which are net borrowers that might need to increase their saving rates in the future.

Table 7, presents the new assets bought by agent based on the assumptions described in the section 2.2.1. Households are the main net lenders which distribute their savings mainly to finance Government and Firms deficits.

Table 7: New assets acquired by agent (as % of GDP) – CPS scenario

		2025	2025	2025	2030	2030	2030	2050	2050	2050
		H	F	G	H	F	G	H	F	G
EU27	TD ⁴	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
EU27	GB	8.7%	0.0%	0.0%	7.7%	0.0%	0.0%	7.0%	0.0%	0.0%
EU27	CB	7.0%	0.0%	0.0%	7.0%	0.0%	0.0%	5.6%	0.0%	0.0%
GBR	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
GBR	GB	3.3%	0.0%	0.0%	3.0%	0.0%	0.0%	3.5%	0.0%	0.0%
GBR	CB	2.6%	0.0%	0.0%	2.7%	0.0%	0.0%	2.8%	0.0%	0.0%
USA	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
USA	GB	1.4%	0.0%	0.0%	0.8%	0.0%	0.0%	1.6%	0.0%	0.0%
USA	CB	1.1%	0.0%	0.0%	0.7%	0.0%	0.0%	1.3%	0.0%	0.0%
JPN	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
JPN	GB	8.1%	0.0%	0.0%	7.3%	0.0%	0.0%	6.9%	0.0%	0.0%
JPN	CB	6.6%	0.0%	0.0%	6.6%	0.0%	0.0%	5.5%	0.0%	0.0%
CAN	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
CAN	GB	6.8%	0.0%	0.0%	5.8%	0.0%	0.0%	5.5%	0.0%	0.0%
CAN	CB	5.5%	0.0%	0.0%	5.2%	0.0%	0.0%	4.5%	0.0%	0.0%
BRA	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
BRA	GB	2.6%	0.0%	1.1%	2.3%	0.0%	1.5%	1.8%	0.0%	1.4%
BRA	CB	2.1%	0.0%	0.9%	2.1%	0.0%	1.4%	1.5%	0.0%	1.2%
CHN	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
CHN	GB	17.2%	0.0%	0.0%	15.5%	0.0%	0.0%	15.3%	0.0%	0.0%
CHN	CB	13.8%	0.0%	0.0%	14.0%	0.0%	0.0%	12.3%	0.0%	0.0%
IND	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
IND	GB	11.7%	0.0%	0.0%	9.4%	0.0%	0.0%	9.8%	0.0%	0.0%

⁴ TD means Time Deposits

IND	CB	9.4%	0.0%	0.0%	8.4%	0.0%	0.0%	7.9%	0.0%	0.0%
KOR	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
KOR	GB	12.9%	0.0%	0.0%	11.0%	0.0%	0.0%	11.5%	0.0%	0.0%
KOR	CB	10.4%	0.0%	0.0%	9.9%	0.0%	0.0%	9.3%	0.0%	0.0%
IDN	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
IDN	GB	14.7%	0.0%	0.0%	12.7%	0.0%	0.0%	11.9%	0.0%	0.0%
IDN	CB	11.8%	0.0%	0.0%	11.5%	0.0%	0.0%	9.6%	0.0%	0.0%
MEX	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
MEX	GB	5.9%	0.0%	0.0%	5.1%	0.0%	0.0%	4.7%	0.0%	0.0%
MEX	CB	4.7%	0.0%	0.0%	4.6%	0.0%	0.0%	3.8%	0.0%	0.0%
ARG	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
ARG	GB	5.1%	0.0%	0.0%	5.0%	0.0%	0.0%	4.7%	0.0%	0.0%
ARG	CB	4.1%	0.0%	0.0%	4.5%	0.0%	0.0%	3.7%	0.0%	0.0%
TUR	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
TUR	GB	5.8%	0.0%	0.0%	6.8%	0.0%	0.0%	9.0%	0.0%	0.0%
TUR	CB	4.6%	0.0%	0.0%	6.1%	0.0%	0.0%	7.3%	0.0%	0.0%
SAR	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
SAR	GB	26.7%	0.0%	0.0%	23.6%	0.0%	0.0%	23.9%	0.0%	0.0%
SAR	CB	21.5%	0.0%	0.0%	21.3%	0.0%	0.0%	19.2%	0.0%	0.0%
OCE	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
OCE	GB	14.1%	0.0%	0.0%	11.8%	0.0%	0.0%	12.0%	0.0%	0.0%
OCE	CB	11.4%	0.0%	0.0%	10.6%	0.0%	0.0%	9.6%	0.0%	0.0%
RUS	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
RUS	GB	14.2%	0.0%	0.0%	12.6%	0.0%	0.0%	12.5%	0.0%	0.0%
RUS	CB	11.5%	0.0%	0.0%	11.4%	0.0%	0.0%	10.1%	0.0%	0.0%
ARE	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
ARE	GB	18.9%	0.0%	0.0%	14.4%	0.0%	0.0%	12.9%	0.0%	0.0%
ARE	CB	15.2%	0.0%	0.0%	13.0%	0.0%	0.0%	10.4%	0.0%	0.0%
REP	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
REP	GB	24.4%	0.0%	0.0%	22.1%	0.0%	0.0%	21.3%	0.0%	0.0%
REP	CB	19.7%	0.0%	0.0%	19.9%	0.0%	0.0%	17.1%	0.0%	0.0%
SAF	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
SAF	GB	8.4%	0.0%	0.0%	8.2%	0.0%	0.0%	7.1%	0.0%	0.0%
SAF	CB	6.8%	0.0%	0.0%	7.4%	0.0%	0.0%	5.7%	0.0%	0.0%
REU	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
REU	GB	11.3%	0.0%	0.0%	10.3%	0.0%	0.0%	9.5%	0.0%	0.0%
REU	CB	9.1%	0.0%	0.0%	9.3%	0.0%	0.0%	7.6%	0.0%	0.0%
ROW	TD	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
ROW	GB	5.4%	0.0%	0.0%	5.5%	0.0%	0.0%	4.7%	0.0%	0.0%
ROW	CB	4.4%	0.0%	0.0%	5.0%	0.0%	0.0%	3.8%	0.0%	0.0%

Source: GEM-E3

2.6 Core Policy Scenario with exogenous additional investments

In the standard version of GEM-E3, a worldwide interest rate is computed by equating total savings with total investment for all countries/regions as a dual value of this restriction. The worldwide interest rate affect the household consumption of all countries and thus their savings.

In this variant of the CPS scenario (**CPS_v1**), the exogenous increase in the investment will increase

the worldwide interest rate so as to decrease household consumption and increase their savings. Table 8 and Table 9 present the results for the additional investment and additional savings in this variant as compared to the CPS scenario, respectively.

Table 8: Investments (% of GDP) – Change from CPS scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
EU27	0.00%	2.26%	2.34%	2.41%	2.49%	2.55%	2.88%	3.19%	3.48%	3.75%
GBR	0.00%	1.83%	1.88%	1.94%	2.00%	2.05%	2.31%	2.57%	2.82%	3.06%
USA	0.00%	1.99%	2.12%	2.24%	2.34%	2.46%	2.88%	3.26%	3.60%	3.91%
JPN	0.00%	2.81%	2.90%	2.96%	3.05%	3.12%	3.47%	3.76%	4.02%	4.24%
CAN	0.00%	2.28%	2.36%	2.44%	2.53%	2.64%	3.02%	3.37%	3.70%	4.03%
BRA	0.00%	1.66%	1.70%	1.73%	1.79%	1.83%	2.04%	2.25%	2.46%	2.67%
CHN	0.00%	4.49%	4.68%	4.88%	5.09%	5.24%	6.07%	6.74%	7.26%	7.64%
IND	0.00%	3.53%	3.75%	3.98%	4.23%	4.44%	5.36%	6.19%	6.88%	7.41%
KOR	0.00%	3.00%	3.10%	3.19%	3.30%	3.39%	3.82%	4.20%	4.53%	4.80%
IDN	0.00%	3.61%	3.77%	3.92%	4.08%	4.23%	4.96%	5.62%	6.19%	6.69%
MEX	0.00%	1.93%	2.01%	2.08%	2.16%	2.24%	2.56%	2.87%	3.16%	3.42%
ARG	0.00%	2.30%	2.49%	2.71%	2.83%	2.92%	3.33%	3.70%	4.03%	4.33%
TUR	0.00%	1.29%	1.23%	1.20%	1.23%	1.25%	1.40%	1.57%	1.74%	1.92%
SAR	0.00%	3.41%	3.67%	3.88%	4.06%	4.30%	4.99%	5.62%	6.10%	6.42%
OCE	0.00%	2.85%	3.00%	3.15%	3.28%	3.38%	3.86%	4.28%	4.70%	5.07%
RUS	0.00%	2.49%	2.66%	2.79%	2.89%	2.96%	3.40%	3.75%	4.05%	4.31%
ARE	0.00%	3.33%	3.47%	3.61%	3.74%	3.86%	4.53%	5.21%	5.83%	6.36%
REP	0.00%	3.39%	3.54%	3.69%	3.81%	3.93%	4.49%	4.99%	5.49%	5.94%
SAF	0.00%	1.64%	1.73%	1.84%	1.91%	1.95%	2.22%	2.49%	2.75%	2.99%
REU	0.00%	2.89%	3.04%	3.18%	3.30%	3.40%	3.91%	4.32%	4.69%	5.01%
ROW	0.00%	2.32%	2.44%	2.55%	2.66%	2.80%	3.11%	3.42%	3.74%	4.05%
WORLD	0.00%	2.77%	2.91%	3.04%	3.18%	3.30%	3.84%	4.30%	4.71%	5.05%

Source: GEM-E3

Table 9: Savings (% of GDP) – Change from CPS scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
EU27	0.00%	2.46%	2.55%	2.64%	2.74%	2.83%	3.21%	3.55%	3.85%	4.08%
GBR	0.00%	2.22%	2.28%	2.33%	2.40%	2.46%	2.78%	3.06%	3.31%	3.54%
USA	0.00%	2.68%	2.74%	2.80%	2.87%	2.93%	3.18%	3.42%	3.64%	3.84%
JPN	0.00%	2.46%	2.58%	2.70%	2.81%	2.92%	3.43%	3.86%	4.25%	4.58%
CAN	0.00%	2.42%	2.50%	2.57%	2.64%	2.71%	3.06%	3.36%	3.63%	3.87%
BRA	0.00%	2.43%	2.50%	2.56%	2.63%	2.70%	3.05%	3.39%	3.70%	3.97%
CHN	0.00%	3.33%	3.56%	3.78%	4.00%	4.19%	4.99%	5.65%	6.20%	6.63%
IND	0.00%	3.23%	3.47%	3.69%	3.90%	4.10%	4.77%	5.33%	5.78%	6.12%
KOR	0.00%	2.68%	2.84%	3.00%	3.16%	3.29%	3.89%	4.40%	4.85%	5.22%
IDN	0.00%	3.18%	3.39%	3.59%	3.78%	3.97%	4.69%	5.33%	5.89%	6.37%
MEX	0.00%	2.94%	3.02%	3.10%	3.18%	3.25%	3.62%	3.95%	4.24%	4.50%
ARG	0.00%	2.04%	2.20%	2.36%	2.54%	2.71%	3.40%	3.99%	4.49%	4.92%
TUR	0.00%	2.89%	2.98%	3.06%	3.13%	3.20%	3.58%	4.02%	4.51%	5.01%
SAR	0.00%	2.31%	2.55%	2.79%	3.05%	3.33%	4.46%	5.48%	6.39%	7.15%
OCE	0.00%	2.26%	2.41%	2.57%	2.72%	2.86%	3.50%	4.05%	4.54%	4.97%
RUS	0.00%	2.32%	2.46%	2.59%	2.73%	2.85%	3.53%	4.13%	4.67%	5.15%

ARE	0.00%	2.61%	2.88%	3.15%	3.42%	3.69%	4.74%	5.69%	6.55%	7.31%
REP	0.00%	2.01%	2.26%	2.52%	2.78%	3.03%	4.17%	5.22%	6.18%	7.06%
SAF	0.00%	2.51%	2.59%	2.68%	2.79%	2.88%	3.43%	3.94%	4.40%	4.78%
REU	0.00%	2.41%	2.58%	2.74%	2.90%	3.04%	3.67%	4.22%	4.69%	5.09%
ROW	0.00%	3.05%	3.15%	3.25%	3.36%	3.46%	3.90%	4.25%	4.57%	4.85%
WORLD	0.00%	2.77%	2.91%	3.04%	3.18%	3.30%	3.84%	4.30%	4.71%	5.05%

Source: GEM-E3

The change in investments depends on their level in the CPS scenario. The change in savings depends on the households' saving rate. Table 10 present the change in deficit or surplus as compared to the CPS scenario.

Table 10: Deficit or Surplus of economic agents by region (% of GDP) – change from CPS scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
EU27	0.00%	0.20%	0.21%	0.23%	0.25%	0.27%	0.32%	0.36%	0.37%	0.33%
GBR	0.00%	0.40%	0.39%	0.39%	0.40%	0.41%	0.47%	0.49%	0.49%	0.48%
USA	0.00%	0.68%	0.62%	0.57%	0.53%	0.47%	0.30%	0.16%	0.04%	-0.07%
JPN	0.00%	-0.35%	-0.31%	-0.27%	-0.24%	-0.20%	-0.04%	0.10%	0.23%	0.33%
CAN	0.00%	0.14%	0.13%	0.13%	0.11%	0.08%	0.04%	-0.01%	-0.07%	-0.16%
BRA	0.00%	0.77%	0.80%	0.83%	0.85%	0.87%	1.00%	1.14%	1.24%	1.31%
CHN	0.00%	-1.15%	-1.12%	-1.10%	-1.09%	-1.05%	-1.08%	-1.08%	-1.06%	-1.01%
IND	0.00%	-0.30%	-0.28%	-0.28%	-0.32%	-0.34%	-0.59%	-0.87%	-1.10%	-1.29%
KOR	0.00%	-0.32%	-0.25%	-0.19%	-0.15%	-0.10%	0.07%	0.20%	0.32%	0.42%
IDN	0.00%	-0.43%	-0.38%	-0.34%	-0.30%	-0.26%	-0.27%	-0.28%	-0.30%	-0.32%
MEX	0.00%	1.01%	1.01%	1.02%	1.01%	1.01%	1.06%	1.08%	1.08%	1.08%
ARG	0.00%	-0.27%	-0.29%	-0.35%	-0.29%	-0.21%	0.06%	0.28%	0.46%	0.60%
TUR	0.00%	1.60%	1.76%	1.86%	1.90%	1.95%	2.17%	2.45%	2.76%	3.08%
SAR	0.00%	-1.10%	-1.12%	-1.09%	-1.01%	-0.97%	-0.53%	-0.14%	0.28%	0.73%
OCE	0.00%	-0.59%	-0.59%	-0.58%	-0.56%	-0.52%	-0.36%	-0.24%	-0.16%	-0.10%
RUS	0.00%	-0.17%	-0.20%	-0.20%	-0.17%	-0.11%	0.13%	0.37%	0.61%	0.84%
ARE	0.00%	-0.73%	-0.59%	-0.45%	-0.31%	-0.17%	0.22%	0.49%	0.72%	0.94%
REP	0.00%	-1.38%	-1.28%	-1.17%	-1.03%	-0.89%	-0.32%	0.23%	0.70%	1.12%
SAF	0.00%	0.87%	0.85%	0.85%	0.88%	0.93%	1.21%	1.45%	1.64%	1.79%
REU	0.00%	-0.48%	-0.46%	-0.45%	-0.40%	-0.35%	-0.23%	-0.11%	0.00%	0.08%
ROW	0.00%	0.73%	0.71%	0.71%	0.71%	0.66%	0.79%	0.83%	0.83%	0.80%
WORLD	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Source: GEM-E3

Additional firms and Government deficit is financed by issuing new Corporate and Government Bonds that are directed to Households. In the standard version of GEM-E3, the allocation of savings doesn't affect future income. Households do not receive any payments back for the amount of money that they lend to other agents.

By adding the financial instruments: Time Deposits, Corporate Bonds and Government Bonds there is an accounting framework of the new assets and liabilities that are generated by agent. This framework allows to build a Debt calculators for better understanding the financial needs by agent in each scenario.

The additional Debt creation in Firms and Government for the additional exogenous investment

assumption is presented in Table 11 and Table 12, respectively.

Table 11: Additional Debt in Firms (as % of GDP) – Change from CPS scenario

	2026	2027	2028	2029	2030	2035	2040	2045	2050
EU27	0.00%	1.26%	2.53%	3.81%	5.11%	12.01%	18.98%	25.81%	32.58%
GBR	0.00%	0.55%	1.10%	1.66%	2.22%	5.20%	8.03%	10.83%	13.69%
USA	0.00%	0.61%	1.24%	1.88%	2.53%	6.12%	9.68%	13.44%	17.39%
JPN	0.00%	0.83%	1.67%	2.51%	3.38%	7.86%	12.28%	16.80%	21.38%
CAN	0.00%	0.68%	1.37%	2.06%	2.77%	6.63%	10.25%	13.88%	17.62%
BRA	0.00%	0.50%	1.00%	1.49%	1.99%	4.64%	6.91%	8.96%	10.87%
CHN	0.00%	1.31%	2.62%	3.93%	5.25%	12.62%	19.30%	26.42%	33.71%
IND	0.00%	1.06%	2.10%	3.14%	4.19%	10.44%	15.67%	21.12%	26.67%
KOR	0.00%	0.88%	1.76%	2.63%	3.50%	8.29%	12.84%	17.59%	22.66%
IDN	0.00%	1.06%	2.10%	3.13%	4.15%	9.99%	15.18%	20.44%	25.89%
MEX	0.00%	0.59%	1.17%	1.75%	2.34%	5.51%	8.18%	10.77%	13.28%
ARG	0.00%	0.68%	1.40%	2.16%	2.92%	7.09%	10.99%	14.83%	18.52%
TUR	0.00%	0.40%	0.75%	1.08%	1.40%	3.16%	4.51%	5.88%	7.29%
SAR	0.00%	0.99%	2.03%	3.11%	4.22%	10.32%	16.00%	22.01%	28.13%
OCE	0.00%	0.84%	1.70%	2.58%	3.47%	8.29%	12.70%	17.10%	21.62%
RUS	0.00%	0.74%	1.52%	2.33%	3.16%	7.46%	11.69%	15.83%	19.92%
ARE	0.00%	0.97%	1.93%	2.88%	3.81%	9.11%	13.51%	18.10%	22.93%
REP	0.00%	0.98%	1.99%	3.02%	4.05%	9.60%	14.77%	19.52%	24.17%
SAF	0.00%	0.49%	0.99%	1.51%	2.04%	4.81%	7.27%	9.55%	11.67%
REU	0.00%	0.85%	1.73%	2.62%	3.52%	8.38%	13.04%	17.67%	22.39%
ROW	0.00%	0.70%	1.39%	2.08%	2.77%	6.71%	9.82%	12.82%	15.76%
WORLD	0.00%	0.92%	1.85%	2.78%	3.73%	8.93%	13.78%	18.70%	23.67%

Source: GEM-E3

Table 12: Additional Debt in Government (as % of GDP) – Change from CPS scenario

	2026	2027	2028	2029	2030	2035	2040	2045	2050
EU27	0.00%	0.00%	0.00%	0.01%	0.02%	0.08%	0.18%	0.41%	0.70%
GBR	0.00%	1.01%	1.96%	2.85%	3.70%	7.95%	10.80%	12.76%	14.10%
USA	0.00%	1.28%	2.50%	3.66%	4.77%	10.54%	14.77%	18.24%	21.14%
JPN	0.00%	1.34%	2.63%	3.85%	5.02%	10.80%	15.06%	18.28%	20.61%
CAN	0.00%	1.18%	2.30%	3.38%	4.44%	9.95%	14.06%	17.41%	20.27%
BRA	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
CHN	0.00%	2.26%	4.42%	6.52%	8.58%	19.80%	28.90%	37.92%	46.59%
IND	0.00%	1.76%	3.44%	5.05%	6.63%	15.85%	22.75%	29.62%	36.47%
KOR	0.00%	1.48%	2.88%	4.21%	5.48%	12.13%	17.26%	21.86%	26.23%
IDN	0.00%	1.83%	3.58%	5.27%	6.90%	16.10%	23.41%	30.22%	36.81%
MEX	0.00%	1.10%	2.16%	3.16%	4.11%	9.09%	12.28%	14.64%	16.35%
ARG	0.00%	1.21%	2.36%	3.46%	4.49%	9.58%	12.42%	13.79%	13.96%
TUR	0.00%	0.72%	1.30%	1.77%	2.16%	4.09%	4.19%	3.17%	1.14%
SAR	0.00%	1.92%	3.89%	5.88%	7.83%	18.37%	26.92%	35.21%	42.90%
OCE	0.00%	1.47%	2.92%	4.34%	5.71%	12.88%	18.35%	23.01%	27.17%
RUS	0.00%	1.33%	2.68%	4.01%	5.30%	11.60%	16.41%	19.99%	22.50%
ARE	0.00%	1.75%	3.41%	4.98%	6.47%	14.49%	19.74%	24.20%	28.07%
REP	0.00%	1.71%	3.41%	5.08%	6.71%	15.14%	21.81%	26.87%	30.96%

SAF	0.00%	0.96%	1.87%	2.73%	3.54%	7.42%	9.50%	10.28%	10.03%
REU	0.00%	1.44%	2.85%	4.21%	5.52%	12.30%	17.48%	21.62%	25.06%
ROW	0.00%	1.28%	2.49%	3.63%	4.70%	10.59%	13.94%	16.24%	17.76%
WORLD	0.00%	1.27%	2.50%	3.69%	4.85%	11.03%	15.93%	20.29%	24.16%

Source: GEM-E3

The additional debt allows the financing of the investment and introducing new liabilities from Government and Firms to Households. In the standard version of GEM-E3, the additional debt doesn't affect future income. Households do not receive any payments back for the amount of money that they lend to other agents. Such assumption affect the distribution of income across agents and regions and thus the household consumption. The effect are more pronounced in cases where only a group of countries increase their investment and part of the financing comes from countries outside of this group.

2.7 Core Policy Scenario with exogenous additional investments and interest payments

Having computed the debt by agent, debt serving interest rates can be applied. In this variant, we introduced an interest rate on Governments' and firms' additional debt. Table 13 and Table 14 present the interest rate payments that should be paid by firms and Governments for debt serving, respectively. An exogenous interest rate -same for governments and firms - of 4% is used. The revenues are directed to the holders of the Corporate and Government bonds, the Households.

Table 13: Interest payments on Corporate Bonds (as % of GDP) – Change from CPS scenario

	2026	2027	2028	2029	2030	2035	2040	2045	2050
EU27	0.00%	0.05%	0.10%	0.15%	0.20%	0.45%	0.69%	0.94%	1.19%
GBR	0.00%	0.02%	0.04%	0.06%	0.09%	0.19%	0.29%	0.39%	0.49%
USA	0.00%	0.02%	0.05%	0.07%	0.10%	0.22%	0.35%	0.49%	0.64%
JPN	0.00%	0.03%	0.07%	0.10%	0.13%	0.29%	0.46%	0.63%	0.81%
CAN	0.00%	0.03%	0.05%	0.08%	0.11%	0.23%	0.36%	0.49%	0.63%
BRA	0.00%	0.02%	0.04%	0.06%	0.08%	0.16%	0.23%	0.30%	0.36%
CHN	0.00%	0.05%	0.10%	0.15%	0.20%	0.42%	0.67%	0.94%	1.21%
IND	0.00%	0.04%	0.08%	0.12%	0.16%	0.32%	0.49%	0.68%	0.87%
KOR	0.00%	0.03%	0.07%	0.10%	0.14%	0.30%	0.47%	0.66%	0.86%
IDN	0.00%	0.04%	0.08%	0.12%	0.16%	0.33%	0.51%	0.70%	0.90%
MEX	0.00%	0.02%	0.05%	0.07%	0.09%	0.19%	0.28%	0.37%	0.46%
ARG	0.00%	0.03%	0.05%	0.08%	0.11%	0.25%	0.38%	0.52%	0.64%
TUR	0.00%	0.02%	0.03%	0.04%	0.05%	0.10%	0.15%	0.21%	0.26%
SAR	0.00%	0.04%	0.08%	0.12%	0.17%	0.36%	0.57%	0.79%	1.02%
OCE	0.00%	0.03%	0.07%	0.10%	0.14%	0.29%	0.44%	0.60%	0.76%
RUS	0.00%	0.03%	0.06%	0.09%	0.13%	0.27%	0.42%	0.57%	0.72%
ARE	0.00%	0.04%	0.07%	0.11%	0.15%	0.29%	0.44%	0.61%	0.79%
REP	0.00%	0.04%	0.08%	0.12%	0.16%	0.34%	0.50%	0.66%	0.82%
SAF	0.00%	0.02%	0.04%	0.06%	0.08%	0.17%	0.24%	0.32%	0.39%
REU	0.00%	0.03%	0.07%	0.10%	0.14%	0.30%	0.46%	0.63%	0.81%
ROW	0.00%	0.03%	0.05%	0.08%	0.11%	0.22%	0.32%	0.43%	0.53%
WORLD	0.00%	0.04%	0.07%	0.11%	0.14%	0.31%	0.48%	0.66%	0.84%

Source: GEM-E3

Table 14: Interest payments on Government Bonds (as % of GDP) – Change from CPS scenario

	2026	2027	2028	2029	2030	2035	2040	2045	2050
EU27	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.01%	0.03%
GBR	0.00%	0.04%	0.08%	0.11%	0.15%	0.28%	0.38%	0.46%	0.51%
USA	0.00%	0.05%	0.10%	0.14%	0.19%	0.38%	0.54%	0.67%	0.78%
JPN	0.00%	0.05%	0.10%	0.15%	0.20%	0.40%	0.56%	0.69%	0.78%
CAN	0.00%	0.05%	0.09%	0.13%	0.18%	0.35%	0.49%	0.62%	0.72%
BRA	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
CHN	0.00%	0.09%	0.17%	0.25%	0.33%	0.67%	1.01%	1.35%	1.67%
IND	0.00%	0.07%	0.13%	0.19%	0.25%	0.48%	0.71%	0.95%	1.19%
KOR	0.00%	0.06%	0.11%	0.16%	0.21%	0.43%	0.63%	0.82%	0.99%
IDN	0.00%	0.07%	0.14%	0.20%	0.26%	0.53%	0.78%	1.03%	1.28%
MEX	0.00%	0.04%	0.08%	0.12%	0.16%	0.31%	0.42%	0.50%	0.56%
ARG	0.00%	0.05%	0.09%	0.14%	0.17%	0.34%	0.43%	0.48%	0.48%
TUR	0.00%	0.03%	0.05%	0.07%	0.08%	0.14%	0.14%	0.11%	0.04%
SAR	0.00%	0.08%	0.15%	0.23%	0.31%	0.64%	0.95%	1.26%	1.55%
OCE	0.00%	0.06%	0.11%	0.17%	0.22%	0.45%	0.64%	0.81%	0.96%
RUS	0.00%	0.05%	0.11%	0.16%	0.21%	0.43%	0.59%	0.72%	0.82%
ARE	0.00%	0.07%	0.13%	0.19%	0.25%	0.46%	0.65%	0.81%	0.96%
REP	0.00%	0.07%	0.13%	0.20%	0.26%	0.53%	0.74%	0.91%	1.05%
SAF	0.00%	0.04%	0.07%	0.11%	0.14%	0.26%	0.32%	0.34%	0.33%
REU	0.00%	0.06%	0.11%	0.16%	0.22%	0.44%	0.62%	0.77%	0.90%
ROW	0.00%	0.05%	0.10%	0.14%	0.18%	0.34%	0.46%	0.54%	0.60%
WORLD	0.00%	0.05%	0.10%	0.14%	0.19%	0.38%	0.56%	0.72%	0.86%

Source: GEM-E3

Debt-serving mechanisms that alter firms and households behavior can be applied to allow the financing of the interest payments that are produced by the agents' debt. In this study we apply the following key mechanisms for Government and Firms:

- **Government:** The interest payments related to Government Bonds will be paid by reducing the Government spending.
- **Firms:** The interest payments related to Corporate Bonds will be paid by cancelling out other investments.

Government Bonds and interest payments

In the CPS scenario with the exogenous additional investments the interest payments from the Government bonds are financed by reducing Government spending. The countries which increases their debt to finance investment through public debt will have a negative impact on their future Government spending. The GDP impact is not significant (see Table 15). The impact of the components of GDP is more profound.

Table 15: GDP – % change from CPS_v1 scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
WORLD	0.0%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.01%	0.02%	0.03%
USA	0.0%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.02%
JPN	0.0%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.01%	0.01%	0.02%
CAN	0.0%	0.00%	0.00%	0.00%	0.00%	0.01%	0.01%	0.02%	0.03%	0.03%
BRA	0.0%	0.00%	0.01%	0.02%	0.03%	0.04%	0.07%	0.10%	0.12%	0.13%

CHN	0.0%	0.00%	0.00%	0.00%	-0.01%	-0.01%	-0.01%	-0.01%	-0.01%	-0.01%
IND	0.0%	0.00%	0.00%	-0.01%	-0.01%	-0.01%	-0.02%	-0.02%	-0.01%	-0.01%
KOR	0.0%	0.00%	0.00%	0.00%	0.00%	0.01%	0.02%	0.03%	0.04%	0.05%
IDN	0.0%	0.00%	-0.01%	-0.01%	-0.02%	-0.02%	-0.04%	-0.05%	-0.05%	-0.04%
MEX	0.0%	0.00%	0.00%	0.00%	-0.01%	-0.01%	-0.01%	0.00%	0.01%	0.03%
ARG	0.0%	0.00%	0.00%	0.00%	0.01%	0.01%	0.02%	0.04%	0.06%	0.07%
TUR	0.0%	0.00%	0.00%	0.01%	0.01%	0.01%	0.03%	0.05%	0.07%	0.11%
SAR	0.0%	0.00%	0.00%	0.00%	-0.01%	-0.02%	-0.03%	-0.03%	-0.04%	-0.02%
OCE	0.0%	0.00%	0.00%	-0.01%	-0.01%	-0.01%	-0.01%	0.00%	0.01%	0.02%
RUS	0.0%	0.00%	0.00%	0.00%	-0.01%	-0.01%	-0.02%	-0.03%	-0.03%	-0.02%
ARE	0.0%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.02%	0.04%	0.06%
REP	0.0%	0.00%	0.00%	0.00%	0.00%	-0.01%	-0.02%	-0.01%	0.00%	0.03%
SAF	0.0%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.04%	0.06%	0.09%
REU	0.0%	0.00%	0.00%	0.00%	0.00%	0.00%	-0.01%	-0.01%	-0.01%	0.00%
ROW	0.0%	0.00%	0.00%	0.00%	0.01%	0.01%	0.02%	0.03%	0.05%	0.07%
EU27	0.0%	0.00%	0.01%	0.01%	0.02%	0.03%	0.05%	0.07%	0.08%	0.09%

Source: GEM-E3

Government spending reduces (Table 16) to secure savings for the interest payments as a result of the Government Bonds issued to finance the additional investment in the CPS_v1 scenario. The interest payments are directed to the holders of the Government Bonds, the Households which increases private consumption (Table 17).

Table 16: Government Expenditures (as % of GDP) – Change from CPS_v1 scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
WORLD	0.0%	0.00%	-0.05%	-0.10%	-0.14%	-0.19%	-0.38%	-0.55%	-0.70%	-0.83%
USA	0.0%	0.00%	-0.05%	-0.10%	-0.14%	-0.19%	-0.38%	-0.54%	-0.67%	-0.78%
JPN	0.0%	0.00%	-0.05%	-0.10%	-0.15%	-0.20%	-0.40%	-0.56%	-0.68%	-0.77%
CAN	0.0%	0.00%	-0.05%	-0.09%	-0.13%	-0.18%	-0.35%	-0.49%	-0.61%	-0.71%
BRA	0.0%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
CHN	0.0%	0.00%	-0.09%	-0.17%	-0.25%	-0.33%	-0.66%	-0.99%	-1.30%	-1.59%
IND	0.0%	0.00%	-0.07%	-0.13%	-0.19%	-0.25%	-0.48%	-0.71%	-0.93%	-1.16%
KOR	0.0%	0.00%	-0.06%	-0.11%	-0.16%	-0.21%	-0.43%	-0.62%	-0.80%	-0.96%
IDN	0.0%	0.00%	-0.07%	-0.14%	-0.20%	-0.26%	-0.53%	-0.78%	-1.01%	-1.25%
MEX	0.0%	0.00%	-0.04%	-0.08%	-0.12%	-0.16%	-0.31%	-0.41%	-0.49%	-0.54%
ARG	0.0%	0.00%	-0.05%	-0.09%	-0.14%	-0.18%	-0.34%	-0.43%	-0.47%	-0.47%
TUR	0.0%	0.00%	-0.03%	-0.05%	-0.07%	-0.08%	-0.14%	-0.14%	-0.11%	-0.04%
SAR	0.0%	0.00%	-0.08%	-0.16%	-0.24%	-0.32%	-0.65%	-0.96%	-1.25%	-1.52%
OCE	0.0%	0.00%	-0.06%	-0.12%	-0.17%	-0.22%	-0.44%	-0.63%	-0.79%	-0.92%
RUS	0.0%	0.00%	-0.05%	-0.11%	-0.16%	-0.22%	-0.44%	-0.60%	-0.73%	-0.82%
ARE	0.0%	0.00%	-0.07%	-0.13%	-0.20%	-0.25%	-0.47%	-0.66%	-0.82%	-0.97%
REP	0.0%	0.00%	-0.07%	-0.14%	-0.20%	-0.27%	-0.54%	-0.75%	-0.92%	-1.05%
SAF	0.0%	0.00%	-0.04%	-0.07%	-0.11%	-0.14%	-0.26%	-0.32%	-0.33%	-0.32%
REU	0.0%	0.00%	-0.06%	-0.11%	-0.16%	-0.22%	-0.44%	-0.62%	-0.77%	-0.90%
ROW	0.0%	0.00%	-0.05%	-0.10%	-0.14%	-0.18%	-0.34%	-0.45%	-0.53%	-0.58%
EU27	0.0%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	-0.01%	-0.02%	-0.03%

Source: GEM-E3

Table 17: Household Consumption (as % of GDP) – Change from CPS_v1 scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
WORLD	0.0%	0.00%	0.05%	0.10%	0.14%	0.19%	0.38%	0.55%	0.71%	0.84%
USA	0.0%	0.00%	0.07%	0.13%	0.20%	0.26%	0.51%	0.72%	0.90%	1.04%
JPN	0.0%	0.00%	0.04%	0.08%	0.11%	0.15%	0.31%	0.47%	0.61%	0.75%
CAN	0.0%	0.00%	0.04%	0.09%	0.13%	0.17%	0.34%	0.49%	0.62%	0.74%
BRA	0.0%	0.00%	0.06%	0.12%	0.18%	0.23%	0.46%	0.66%	0.82%	0.96%
CHN	0.0%	0.00%	0.04%	0.07%	0.11%	0.14%	0.29%	0.42%	0.55%	0.65%
IND	0.0%	0.00%	0.05%	0.10%	0.14%	0.19%	0.38%	0.54%	0.66%	0.75%
KOR	0.0%	0.00%	0.04%	0.07%	0.11%	0.15%	0.31%	0.46%	0.61%	0.75%
IDN	0.0%	0.00%	0.04%	0.09%	0.13%	0.17%	0.36%	0.53%	0.68%	0.82%
MEX	0.0%	0.00%	0.06%	0.12%	0.17%	0.23%	0.45%	0.65%	0.83%	0.98%
ARG	0.0%	0.00%	0.04%	0.07%	0.10%	0.13%	0.28%	0.43%	0.57%	0.70%
TUR	0.0%	0.00%	0.06%	0.13%	0.19%	0.24%	0.47%	0.66%	0.84%	1.01%
SAR	0.0%	0.00%	0.03%	0.05%	0.07%	0.09%	0.20%	0.33%	0.45%	0.58%
OCE	0.0%	0.00%	0.03%	0.06%	0.08%	0.11%	0.23%	0.36%	0.47%	0.58%
RUS	0.0%	0.00%	0.04%	0.07%	0.11%	0.14%	0.29%	0.43%	0.56%	0.68%
ARE	0.0%	0.00%	0.04%	0.07%	0.11%	0.15%	0.32%	0.51%	0.69%	0.87%
REP	0.0%	0.00%	0.02%	0.04%	0.05%	0.07%	0.16%	0.27%	0.38%	0.50%
SAF	0.0%	0.00%	0.05%	0.10%	0.14%	0.18%	0.38%	0.57%	0.74%	0.90%
REU	0.0%	0.00%	0.03%	0.07%	0.10%	0.13%	0.28%	0.43%	0.56%	0.68%
ROW	0.0%	0.00%	0.07%	0.13%	0.19%	0.24%	0.48%	0.70%	0.88%	1.04%
EU27	0.0%	0.00%	0.04%	0.08%	0.12%	0.15%	0.33%	0.50%	0.66%	0.82%

Source: GEM-E3

Corporate Bonds and interest payments

In the CPS scenario with the exogenous additional investments the interest payments from the Corporate bonds are used to crowd out other investments. The countries which increases their debt to finance investment through private debt will have a negative impact on their future investment. The GDP impact of cancelling out other investment in not significant in the short-term but the negative impact increases in the long-term due to the lower capital stock that the lower investment imply (see Table 18).

Table 18: GDP – % change from CPS_v1 scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
WORLD	0.0%	0.00%	0.00%	-0.01%	-0.02%	-0.03%	-0.11%	-0.29%	-0.56%	-0.94%
USA	0.0%	0.00%	0.00%	0.00%	0.00%	-0.01%	-0.05%	-0.17%	-0.37%	-0.66%
JPN	0.0%	0.00%	0.00%	0.00%	-0.01%	-0.02%	-0.09%	-0.23%	-0.46%	-0.79%
CAN	0.0%	0.00%	0.00%	0.00%	-0.01%	-0.02%	-0.06%	-0.16%	-0.32%	-0.54%
BRA	0.0%	0.00%	0.00%	0.00%	0.00%	-0.01%	-0.05%	-0.16%	-0.33%	-0.58%
CHN	0.0%	0.00%	0.00%	-0.01%	-0.03%	-0.05%	-0.15%	-0.34%	-0.64%	-1.05%
IND	0.0%	0.00%	0.00%	-0.01%	-0.02%	-0.04%	-0.13%	-0.31%	-0.56%	-0.89%
KOR	0.0%	0.00%	0.00%	-0.01%	-0.02%	-0.03%	-0.10%	-0.25%	-0.49%	-0.83%
IDN	0.0%	0.00%	0.00%	-0.01%	-0.02%	-0.04%	-0.13%	-0.33%	-0.65%	-1.10%
MEX	0.0%	0.00%	0.00%	0.00%	-0.01%	-0.02%	-0.09%	-0.25%	-0.50%	-0.86%
ARG	0.0%	0.00%	0.00%	-0.01%	-0.01%	-0.03%	-0.11%	-0.28%	-0.55%	-0.92%
TUR	0.0%	0.00%	0.00%	0.00%	-0.01%	-0.02%	-0.07%	-0.22%	-0.46%	-0.80%
SAR	0.0%	0.00%	0.00%	-0.01%	-0.02%	-0.04%	-0.14%	-0.36%	-0.70%	-1.17%

OCE	0.0%	0.00%	0.00%	-0.01%	-0.02%	-0.03%	-0.11%	-0.25%	-0.48%	-0.80%
RUS	0.0%	0.00%	0.00%	0.00%	-0.01%	-0.03%	-0.10%	-0.27%	-0.54%	-0.91%
ARE	0.0%	0.00%	0.00%	-0.01%	-0.02%	-0.04%	-0.15%	-0.37%	-0.74%	-1.25%
REP	0.0%	0.00%	0.00%	-0.01%	-0.02%	-0.05%	-0.16%	-0.38%	-0.72%	-1.18%
SAF	0.0%	0.00%	0.00%	0.00%	-0.01%	-0.02%	-0.09%	-0.24%	-0.48%	-0.82%
REU	0.0%	0.00%	0.00%	-0.01%	-0.02%	-0.03%	-0.10%	-0.26%	-0.51%	-0.86%
ROW	0.0%	0.00%	0.00%	0.00%	-0.01%	-0.02%	-0.10%	-0.26%	-0.52%	-0.87%
EU27	0.0%	0.00%	0.00%	-0.01%	-0.03%	-0.05%	-0.19%	-0.48%	-0.92%	-1.51%

Source: GEM-E3

Investment reduces (Table 19) to secure savings for the interest payments as a result of the Corporate Bonds issued to finance the additional investment in the CPS_v1 scenario. The interest payments are directed to the holders of the Corporate Bonds, the Households which increases private consumption (Table 20). Household consumption increases due to the additional income but this diminishes in the long-term due to the cumulative impact of the crowding out of other investment that the interest payments imply.

Table 19: Investment (as % of GDP) – Change from CPS_v1 scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
WORLD	0.0%	0.00%	-0.03%	-0.07%	-0.11%	-0.16%	-0.37%	-0.64%	-0.97%	-1.37%
USA	0.0%	0.00%	-0.02%	-0.05%	-0.08%	-0.11%	-0.26%	-0.47%	-0.73%	-1.04%
JPN	0.0%	0.00%	-0.03%	-0.07%	-0.10%	-0.14%	-0.34%	-0.59%	-0.89%	-1.25%
CAN	0.0%	0.00%	-0.03%	-0.05%	-0.09%	-0.12%	-0.27%	-0.47%	-0.71%	-1.00%
BRA	0.0%	0.00%	-0.02%	-0.04%	-0.06%	-0.08%	-0.18%	-0.30%	-0.44%	-0.59%
CHN	0.0%	0.00%	-0.05%	-0.10%	-0.16%	-0.23%	-0.52%	-0.93%	-1.43%	-2.02%
IND	0.0%	0.00%	-0.04%	-0.08%	-0.13%	-0.17%	-0.39%	-0.68%	-1.04%	-1.47%
KOR	0.0%	0.00%	-0.03%	-0.07%	-0.11%	-0.15%	-0.35%	-0.62%	-0.96%	-1.36%
IDN	0.0%	0.00%	-0.04%	-0.08%	-0.13%	-0.17%	-0.40%	-0.70%	-1.08%	-1.54%
MEX	0.0%	0.00%	-0.02%	-0.05%	-0.07%	-0.10%	-0.22%	-0.37%	-0.56%	-0.78%
ARG	0.0%	0.00%	-0.03%	-0.06%	-0.09%	-0.13%	-0.30%	-0.53%	-0.79%	-1.10%
TUR	0.0%	0.00%	-0.01%	-0.03%	-0.04%	-0.05%	-0.12%	-0.19%	-0.29%	-0.41%
SAR	0.0%	0.00%	-0.04%	-0.08%	-0.13%	-0.19%	-0.44%	-0.77%	-1.20%	-1.69%
OCE	0.0%	0.00%	-0.03%	-0.07%	-0.11%	-0.15%	-0.35%	-0.59%	-0.90%	-1.27%
RUS	0.0%	0.00%	-0.03%	-0.06%	-0.10%	-0.14%	-0.32%	-0.55%	-0.84%	-1.17%
ARE	0.0%	0.00%	-0.04%	-0.08%	-0.12%	-0.17%	-0.36%	-0.62%	-0.96%	-1.37%
REP	0.0%	0.00%	-0.04%	-0.08%	-0.13%	-0.18%	-0.41%	-0.69%	-1.03%	-1.41%
SAF	0.0%	0.00%	-0.02%	-0.04%	-0.06%	-0.09%	-0.19%	-0.32%	-0.47%	-0.65%
REU	0.0%	0.00%	-0.03%	-0.07%	-0.11%	-0.15%	-0.36%	-0.62%	-0.95%	-1.34%
ROW	0.0%	0.00%	-0.03%	-0.05%	-0.08%	-0.12%	-0.26%	-0.44%	-0.65%	-0.90%
EU27	0.0%	0.00%	-0.05%	-0.10%	-0.16%	-0.22%	-0.52%	-0.88%	-1.30%	-1.79%

Source: GEM-E3

Table 20: Household Consumption (as % of GDP) – Change from CPS_v1 scenario

	2025	2026	2027	2028	2029	2030	2035	2040	2045	2050
WORLD	0.0%	0.00%	0.03%	0.07%	0.10%	0.13%	0.26%	0.35%	0.41%	0.43%
USA	0.0%	0.00%	0.05%	0.10%	0.15%	0.20%	0.38%	0.50%	0.56%	0.54%
JPN	0.0%	0.00%	0.03%	0.05%	0.07%	0.10%	0.21%	0.31%	0.40%	0.45%
CAN	0.0%	0.00%	0.03%	0.06%	0.09%	0.11%	0.24%	0.35%	0.44%	0.50%

BRA	0.0%	0.00%	0.04%	0.08%	0.12%	0.15%	0.30%	0.41%	0.47%	0.48%
CHN	0.0%	0.00%	0.02%	0.05%	0.07%	0.09%	0.19%	0.30%	0.40%	0.49%
IND	0.0%	0.00%	0.03%	0.07%	0.10%	0.13%	0.26%	0.35%	0.42%	0.44%
KOR	0.0%	0.00%	0.02%	0.05%	0.07%	0.09%	0.20%	0.31%	0.41%	0.50%
IDN	0.0%	0.00%	0.03%	0.06%	0.09%	0.12%	0.25%	0.37%	0.45%	0.49%
MEX	0.0%	0.00%	0.05%	0.09%	0.13%	0.17%	0.33%	0.44%	0.49%	0.48%
ARG	0.0%	0.00%	0.02%	0.05%	0.07%	0.09%	0.18%	0.25%	0.29%	0.28%
TUR	0.0%	0.00%	0.04%	0.09%	0.13%	0.17%	0.32%	0.44%	0.52%	0.57%
SAR	0.0%	0.00%	0.01%	0.03%	0.04%	0.06%	0.13%	0.22%	0.32%	0.43%
OCE	0.0%	0.00%	0.02%	0.04%	0.05%	0.07%	0.15%	0.25%	0.34%	0.42%
RUS	0.0%	0.00%	0.02%	0.05%	0.07%	0.09%	0.20%	0.30%	0.39%	0.46%
ARE	0.0%	0.00%	0.02%	0.04%	0.06%	0.08%	0.18%	0.27%	0.34%	0.36%
REP	0.0%	0.00%	0.01%	0.02%	0.03%	0.04%	0.09%	0.16%	0.24%	0.32%
SAF	0.0%	0.00%	0.03%	0.07%	0.10%	0.13%	0.25%	0.37%	0.44%	0.47%
REU	0.0%	0.00%	0.02%	0.05%	0.07%	0.09%	0.20%	0.30%	0.38%	0.45%
ROW	0.0%	0.00%	0.05%	0.09%	0.13%	0.17%	0.33%	0.45%	0.50%	0.48%
EU27	0.0%	0.00%	0.02%	0.05%	0.06%	0.08%	0.16%	0.18%	0.14%	0.02%

Source: GEM-E3

2.8 Discussion and Conclusions

In this study, we provide an extension of the GEM-E3 Computable General Equilibrium (CGE) model to incorporate a dedicated financial module. This extension allows to implement a more comprehensive analysis of climate policy impacts and transition risks. By introducing the financial accounts, we extend the capacity of the model to capture complex interactions between financial systems and climate mitigation pathways. Assumptions on agents behaviour and on an accounting are presented which allows to depict the new assets and new liabilities and the debt accumulation by economic agent.

The model can be extended to cover additional dynamics. Possible extensions are (1) introduce the debt service via increasing government revenues through taxation, (2) the accounting can be extended to cover financial accounts by origin and destination through bilateral financial accounting matrices, (3) differentiate interest rates based on the credit profile of agents, (4) introducing credit constraints and financial frictions, among others.

The extensions covered within study and the possible extensions are of significant importance on modelling the transition risk. The impact if the investment are financing via public or private debt has different dynamics. The income allocation varies depending on the assumptions regarding the investment financing. Such dynamics becomes important in analysis of climate policies that give a signal to investors to increase investments in green technologies which influence financial stability, sectoral reallocation of capital, and the emergence of transition risks, including systemic vulnerabilities. They also enables the assessment of climate finance strategies, such as concessional lending and blended finance, and their role in unlocking low-carbon investments, particularly in developing economies.

Our scenario analysis demonstrates that financial constraints and the introduction of the financial accounts significantly affect the pace and the distribution of decarbonization, underscoring the need for integrated policy design.

3 Extending WITCH: Adding a financial and short term economic model based on an agent-based model through coupling

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The full paper is included in the Appendix.

This study presents the first coupling of a process-based Integrated Assessment Model (WITCH) with a macroeconomic agent-based model (DSK) to examine the macro-financial implications of deep decarbonization pathways. The research reveals that rapid and ambitious carbon pricing needed to achieve 1.5°C and 2°C climate targets generates significant macroeconomic and financial disruptions, including temporary stagflation and distributional challenges. However, coordinated monetary and fiscal policies can substantially mitigate these transition risks.

3.1 Methodology and Model Integration

The study employs a novel soft-coupling approach linking the World Induced Technical Change Hybrid (WITCH) model with the Dystopian Schumpeter Meeting Keynes (DSK) agent-based model. The WITCH model generates detailed energy transition pathways and carbon tax trajectories for three alternative climate policy scenarios: Current Policy (CP), 2°C target (1000 GtCO₂ budget), and 1.5°C target (500 GtCO₂ budget) in line with the Paris Agreement goals. These outputs feed into DSK, which simulates macroeconomic dynamics at business cycle frequency.

The DSK model features seven agent types across five markets, including heterogeneous firms in consumption and capital goods sectors, a banking system, households, government, central bank, and an eight-technology energy sector. This framework enables analysis of real-financial interactions, balance sheet dynamics, and financial and distributional effects typically absent from conventional climate-economy models.

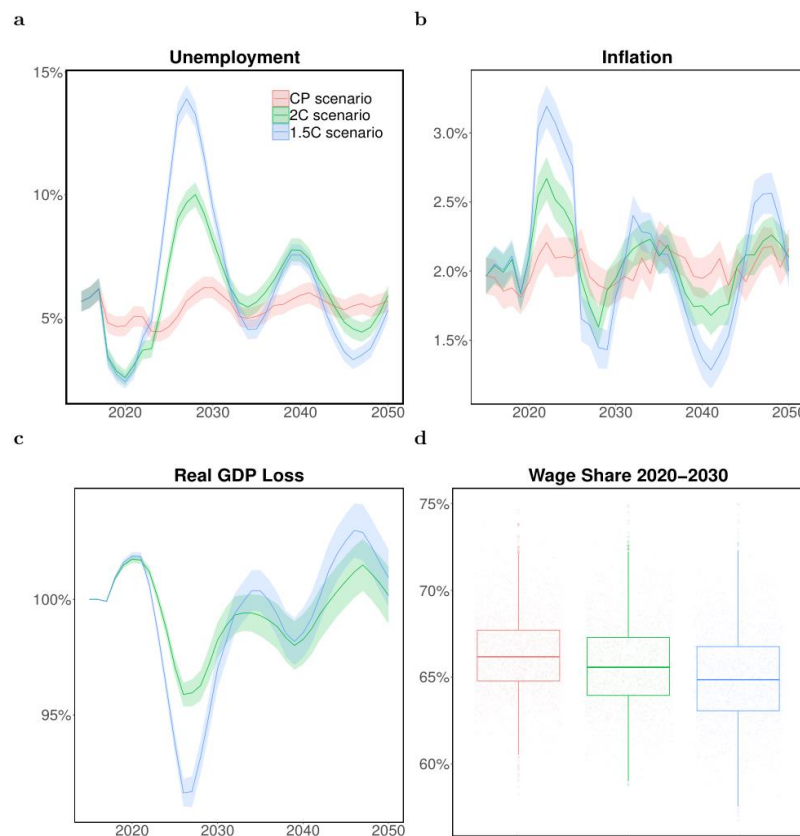


Figure 1 Macroeconomic dynamics induced by different mitigation pathways.

3.2 Key Findings

3.2.1 Macroeconomic Disruptions

The analysis reveals that ambitious climate targets would result in sharp increases in energy prices driven by high carbon pricing, particularly for the 1.5°C scenario where fossil fuel phase-out occurs rapidly. This generates temporary but severe macroeconomic disruptions characterized by stagflationary dynamics where both Paris-aligned climate transition scenarios produce periods of high unemployment reaching 10-15% at the global level (compared to about 5% in the Current Policy scenario) combined with elevated inflation of 2.5-3% (compared to about 2% in the CP scenario), resembling historical stagflationary episodes. The 1.5°C scenario shows more pronounced effects than the 2°C pathway driven by the more rapid and ambitious mitigation efforts, see Figure 1.

The distributional impacts prove equally significant, as carbon pricing substantially reduces the wage share of income, declining from approximately 67% in the CP scenario to 62-64% during the transition period of 2020-2030. This reflects a redistribution of income from labor to government through carbon tax revenue and green energy sectors. Accompanying these distributional shifts, real GDP experiences temporary contraction, with both scenarios showing 4-7% losses relative to the Current Policy baseline during peak transition years.

3.2.2 Energy Sector Dynamics and Financial Stability

The research identifies significant financial imbalances within the energy sector during transition, particularly regarding credit demand as total energy sector credit requirements increase substantially during the transition, reaching 0.6-0.8 trillion USD by 2030, driven primarily by renewable energy capacity expansion and other capital-intensive low-carbon infrastructure and technologies. Asset stranding emerges as a critical concern, with fossil fuel sectors, particularly coal, facing severe financial stress. Coal sector default rates reach 10-20% for the 2°C and 1.5°C scenarios respectively, while oil and gas show more limited exposure.

The capacity utilization patterns reveal another source of instability, as fossil fuel sectors maintain costly spare capacity while simultaneously paying carbon taxes, thereby eroding their profitability and increasing bankruptcy risk throughout the transition period.

3.2.3 Transmission Mechanisms

The study identifies several key transmission channels linking energy transitions to macroeconomic outcomes. Cost pass-through represents the most direct mechanism, as energy price shocks translate immediately to general inflation through escalated production costs. Wage dynamics create important feedback loops, with nominal wages responding to both inflation and labor market conditions simultaneously. The aggregate demand channel operates through reduced wage share leading to lower household consumption due to differential saving propensities between wage and profit income. Finally, the financial accelerator mechanism amplifies these effects as the energy sector stress affects credit provision and overall financial stability.

3.3 Policy Implications

3.3.1 Fiscal Policy Effectiveness

Carbon tax revenue redistribution proves highly effective in mitigating transition costs, particularly during the 2020-2030 decade when carbon tax revenues reach their highest levels. Redistributing revenues to households as lump-sum transfers can reduce average unemployment by 2-4 percentage points while maintaining aggregate demand during energy price shocks and addressing distributional concerns while supporting macroeconomic stability.

3.3.2 Monetary Policy Complementarity

Modified monetary policy rules that respond to increased unemployment alongside inflation show effectiveness in later transition phases, specifically during 2030-2040. When unemployment exceeds threshold levels, accommodative monetary policy can reduce joblessness without generating additional inflationary pressure, since transition-period inflation stems primarily from exogenous energy prices rather than demand pressures.

3.3.3 Policy Coordination Benefits

The analysis demonstrates strong complementarity between fiscal and monetary interventions in the context of clean energy transition. Optimal outcomes occur when high redistribution of 70-90% of the overall carbon tax revenues combines with responsive monetary policy characterized by central bank reactivity coefficients of 1.0-1.8. This

coordination minimizes both unemployment, achieving 5-6% averages (no increase from the Baseline Current Policy scenario), and fiscal costs simultaneously.



4 Innovation and carbon taxes nexus in the DSGE model

The case of implementation of R&D module in global DSGE model

4.1 Introduction

The economic analysis of climate change has historically been dominated by integrated assessment models (IAMs), derived from the groundbreaking Dynamic Integrated Climate-Economy (DICE) model (Nordhaus, 1992). These models were fundamental in building a theoretical bridge between the predictions of geophysical climate models and economic modeling. The main contribution of the first generation of IAMs was to estimate the social cost of emissions—the amount of welfare lost due to greenhouse gas emissions. However, this has been the subject of much controversy due to the crucial assumptions made in these models regarding the social discount rate (Stern, 2007; Nordhaus, 2007), risk aversion, and the treatment of uncertainty, particularly regarding the possibility of future climate tipping points (Weitzman, 2009; Pindyck, 2013).

In their original form, IAM models were a hybrid of deterministic Ramsey-type economic growth models and macroeconometric multi-equation models based on a solid empirical foundation, in which selected model equations were statistically estimated based on empirical data. The most important research deriving from IAM models was their combination with large-scale computable general equilibrium (CGE) models. This was intended to examine the interactions between economic policy and greenhouse gas emissions, and consequently, climate warming and its impact on welfare. The most important advantage of this approach was that it offered—at the price of certain simplifications—detailed sectoral and international disaggregations, while simultaneously strengthening the models' theoretical framework. This enabled IAM + CGE hybrids to become the basis for economic analyses conducted within the framework of the Intergovernmental Panel on Climate Change (Clarke et al., 2014). However, a certain limitation is their deterministic modeling of economic phenomena, which assumes that market participants have full knowledge of both the current and past structure of the economy, as well as its future. This class of models begins with the Arrow-Debreu equilibrium, in which all markets are in equilibrium, meaning supply and demand are equalized through price adjustment. This prevents fully accurate modeling of certain economic phenomena, such as unemployment, information asymmetry, or uncertainty. Public intervention shapes a new equilibrium through the interactions of consumers and producers in the labor, goods, and money markets, etc.

Dynamic stochastic general equilibrium (DSGE) models, a natural generalization of CGE models, are based on the same premise. Unlike their cousins, they adhere to the principle of agent-driven decision-making based strictly on intertemporal optimization under conditions of uncertainty and a range of constraints: resource, technological, institutional, and budgetary. This allows for the modeling of complex market contracts based on microfoundations, thus reflecting non-equilibrium phenomena such as unemployment, as well as analyzing the differences between the economic impact of unexpected, expected, and partially expected phenomena. In the last decade or so, DSGE models have also begun to be applied to climate issues. The original DSGE model, the real business cycle model, was extended by Heutel (2012) to include carbon dioxide emissions. He was followed by (Golosov et al., 2014, Farmer et al., 2015, and Hassler and Krusell, 2018), who, among other things, introduced multiple

sectors following the example of CGE models. The issue of optimal taxation was analyzed by Finkelstein, Shapiro, and Metcalf, 2023, also taking into account the labor market imperfections characteristic of new Keynesian models (cf. Smets and Wouters, 2007). In turn, the issue of modeling inequality in DSGE models with a climate component was recently addressed by Rezai and van der Ploeg, 2017, Benmir and Roman, 2022, and Langot et al., 2023. Finally, many models developed in central banks were also devoted to examining the interaction between climate change and monetary policy, especially the importance of nominal rigidities for the propagation of climate shocks, including the so-called green inflation (e.g. Di Dio, 2015, Diluio et al., 2021 and Del Negro et al., 2023).

An important macroeconomic issue that IAM models, both those constructed within the CGE and DSGE paradigms, attempt to address is the interdependence between climate policy, climate change, and R&D expenditures and innovation. In this respect, endogenous economic growth models provide a theoretical foundation (e.g., Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992; Jones, 1995). These models indicate that knowledge accumulation generates positive externalities because it is a public good, meaning that firms can, at most, exploit a portion of the full social benefits derived from the innovations they create. As a result, they typically invest less than would be socially optimal, which can lead to inefficiency and is supported by empirical evidence (Griliches, 1992; Jones and Williams, 1998). In the climate context, it is also important to note that without appropriate policy, innovation may be suboptimally structured, not only in terms of pace but also in terms of direction, for example, by over-promoting traditional, emission-intensive technologies. For example, Popp (2002) points out that R&D subsidies and other forms of public support for private innovation are essential to reducing the long-term social costs of energy transition, arguing that for society to benefit from the public component of research and development, some economic entities must bear the investment costs and obtain a profit despite the risks, which may require public intervention.

Funding research and development requires the government to generate adequate revenue. Therefore, the interaction between Pigouvian taxes (1920)—such as the carbon tax—and research-supporting policies is an interesting issue. A turning point in this area was the work of Acemoglu et al. (2016), which analyzed them using a deterministic model of directed technological change. The main conclusion of this article is that the need to avoid high costs of future global warming implies large, upfront subsidies for research and development, aimed at accelerating the development of technological inventions necessary for the creation of a climate-neutral economy in the current century. These expenses would initially be higher, then gradually decline, and the rapid implementation of the resulting innovations would be supported by an increasing carbon tax. The combination of a carbon tax and no-R&D subsidies simultaneously addresses the problems of the lack of internalization of negative environmental externalities and the positive impact of already acquired knowledge and experience across the global community of companies. It is worth emphasizing that currently, most deterministic general equilibrium models attempt to describe the private knowledge creation sector, in which firms buy and sell their own technologies, earning profits similarly to other types of activities. The models also attempt to account for externalities of accumulated knowledge, stemming, for example, from the overall level of accumulated know-how worldwide or learning-by-doing (see Coe and Helpman, 1995; Guellec and De la Potterie, 2001; Ghosh, 2007; Bor, Chuang, Lai, and Yang, 2010). An apt distinction can be found in Varga, Pontikakis, and Chorafakis (2014), who distinguish between market-oriented research and strictly scientific research. These authors point out that the most effective policies supporting



each type of R&D activity may differ. They follow Kristkov's (2013) article, which argues that the public R&D sector generates general knowledge, which enters both public and private innovation processes as a specific factor of production. In this way, theoretical models attempt to address the observation that countries in practice use various mechanisms to support innovation: patents, which support the privatization of profits, and subsidies, which support its dissemination.

This article addresses these problems by presenting a quantitative analysis of four innovation scenarios in the global DSGE model with climate change. In the following sections, we discuss: 1) the adopted modeling strategy, 2) the assumptions of the analyzed scenarios, 3) the simulation results (analysis of the impact of innovation and carbon taxes on the economy world economy), and 4) Summary, policy-relevant insights and conclusions.

4.2 Model Structure

4.2.1 Households

Households are characterized by a two-factor utility function (consumption and leisure), which they maximize in the lifetime horizon, using savings that allow them to postpone consumption. Households maximize the discounted expected utility from consumption and leisure time by also investing in human capital.

$$\max U^0 \quad \bar{U}_t = u_t + \beta * E_t[\Lambda_{t+1} \bar{\Pi}_{t+1}]$$

with instantaneous utility belonging to the CRRA class function. Subject to budget constraint

$$P_t^C C_t = W_t * L_t + \dots$$

Where multi-dot symbol denotes other elements of household budget constraint including transfers, purchase and sales of government bonds, net taxes, search costs etc.

In this basis, they determine the supply of labour (in intensive and extensive terms), consumer demand, the size of bank deposits, the demand for money and the value of government bonds held (domestic and foreign). The non-Walrasian labour market allows households and firms to negotiate wages and working hours (sectoral and by firm size) and affects the intensity of searches among the unemployed. Consumption and income from labor and capital remain taxed, the government provides households with social transfers, and public consumption provides them with positive externalities.

4.2.2 Labor market

The labour market reflects a search and matching mechanism in which employers open vacancies and the unemployed seek employment. The model therefore contains labour market equations describing the demand and supply of labour in an imperfect competition for jobs. As a result of the intermediation process, there are fewer vacancies filled than the employees for whom employers report demand, and fewer than it would result from the supply of the unemployed. Wages on the labour market, the subject of which is the expected hourly working time and wages in the future, are negotiated according to the Nash scheme, which is strongly individualistic (both on the part of companies and households). The negotiations take into account the impact of the new wages and working hours on consumption and leisure time in households, and thus on the usability of workers. By combining the supply and demand for labour in the model, the relationship between employment and wages is clearly determined as

well as unemployment.

4.2.3 Firms

Companies decide on the supply and demand for intermediate goods, the level of inventories, the volume of investments and the demand for labour. The company's optimization problem is about maximizing the expected value of the future cash flow stream.

$$\max \Pi^0 \quad \bar{\Pi}_t = \Pi_t + E_t[\Lambda_{t+1} \bar{\Pi}_{t+1}]$$

Talking into account standard budget constraint and production function.

Production of the basic good Y_t takes a form of a nested KLEM process when capital and energy CES bundle (KE) is combined by CES aggregator with labour.

$$KE_t = \left[(\theta_E)^{\frac{1}{\eta_E}} (K_t)^{\frac{\eta_E-1}{\eta_E}} + (1 - \theta_E)^{\frac{1}{\eta_E}} (Z_t * E_t)^{\frac{\eta_E-1}{\eta_E}} \right]^{\frac{\eta_E}{\eta_E-1}}$$

$$Y_t = \left[(\theta_{KE})^{\frac{1}{\eta_{KE}}} (KE_t)^{\frac{\eta_{KE}-1}{\eta_{KE}}} + (1 - \theta_{KE})^{\frac{1}{\eta_{KE}}} (L_t)^{\frac{\eta_{KE}-1}{\eta_{KE}}} \right]^{\frac{\eta_{KE}}{\eta_{KE}-1}}$$

With budget constraint maximizing profits, the share parameters could vary in time in response to shocks or to R&D process. The investment process constitutes of 5-stages, which introduce a significant share of real and nominal frictions into the model (basic product, differentiation based on monopolistic competition, aggregation into a sectoral good, aggregation into final goods). The volume of supply of the final good reflects that consumed by households and the government domestically. Some of the operating costs of companies are financed with debt (operating loans and investment loans). In addition, the incomplete capital market affects the distribution of profit between households (dividends) and future investments, as well as the number of newly created companies and new ideas enabling to reduce emissions (R&D sector). The demand for labour finds an outlet in the vacancies opened and in the wage rates to which the interested members of households agree.

4.2.4 Energy and fuels

Special, separate sector is energy and fuel that combines – once again in the CES bundle - green capital with fossil fuels to produce a single energy good.

$$ENG_t = \left[(\theta_{ENG})^{\frac{1}{\eta_{ENG}}} (A_t^{GC} GC_t)^{\frac{\eta_{ENG}-1}{\eta_{ENG}}} + (1 - \theta_{ENG})^{\frac{1}{\eta_{ENG}}} (A_t^{FF} FF_t)^{\frac{\eta_{ENG}-1}{\eta_{ENG}}} \right]^{\frac{\eta_{ENG}}{\eta_{ENG}-1}}$$

We assume fossil fuels are produced from a resource supply that is perfectly elastic at a normalized price of one. However, its use generates carbon emissions that are taxed by the government diminishing profits of the energy producers. Carbon tax is levied on each unit of fossil fuel used in energy production. At the same time green capital is accumulated in a standard capital accumulation process but the cost of acquiring a new unit of capital good depends on the overall accumulated green capital i.e. there are positive externalities from the green capital accumulation.

4.2.5 Research and development and climate

We assume that in the energy sector directed technological change towards green technologies takes place i.e. Firms accumulate a stock of **R&D (intangible) capital** that raises their own TFP and (partly) **spills over** to others; in equilibrium, each firm ignores the external component.

$$A_t^{GC} = (1 - \delta_R)A_{t-1}^{GC} + A_t^\varphi R_{i,t}$$

Where **R&D efficiency** depends on the aggregate stock of capital. For fossil fuel equation is similar but in this paper we assume that there is no research in this subsector as there is a directed technological change towards green capital. We also – as an option - separate the **creation** of technologies from their **adoption**. R&D expands the stock of *available* blueprints whereas firms choose adoption intensity to convert them into *used* varieties.

4.2.6 Climate

Climate is modelled taking into account the carbon cycle in the form

$$M_t^A = (1 - \delta_M)M_{t-1}^A + CO2_t$$

Where amount of emitted CO2 depends on fossil fuel in use. Radiative forcing takes form

$$F_t = \xi \log M_{t-1} / M_{ss}$$

With

$$T_t = \rho_T * T_{t-1} + \kappa F_t$$

And damage

$$D_t = 1 / (1 + \psi_F(T^\zeta))$$

That translates to lower technology via technology shock:

$$Z_t = Z_T^B * D_t$$

Where Z_t affects productivity of labor and henceforth the GDP.

4.2.7 Public sector

The role of government is revealed in fiscal and monetary functions. Government revenues are financed by taxes (imposed on consumption, labour and capital, and pollution, i.e. PIT, CIT, VAT, social contributions and CO2 fees) as well as from the issue of new bonds, expenditures, in turn, are reduced to public consumption, public investments and transfers (both dependent on other variables of the model, e.g. unemployment benefits resulting from the unemployment rate as well as discretionary transfers (including the policy of subsidies for companies), and the redemption of bonds. Public debt is modelled on the basis of the literature on limitations in the formation of public debt – the increasing cost of servicing it implicitly causes the introduction of restrictions in the model.

Part the government consists of the bank being the issuer of cash and loans provider for operating and investment activities, with companies taking loans subject to liquidity

constraints depending on their size and sector. In the case of the banking sector, money creation is possible. Monetary policy is conducted through open market operations and the creation of high-power money in the course of exogenously set monetary policy. Monetary policy in the model is determined by Taylor's rule, estimated econometrically and causes inflation.

4.3 Model parameters and solution

The parameters of the model can be divided into three groups: (1) The first group includes parameters that determine the level of variables in the steady state. (2) The second class consists of parameters that control the response of variables to shocks. (3) The third group consists of parameters describing the nature of these shocks from the perspective of economic operators.

The first class of model parameters – covering about 80% of all – are parameters determining long-term relationships between macroeconomic variables, in the area of macroeconomic accounts (global production, value added, consumption, investments), in the area of the labor market (employment, unemployment, wages) or in the area of public finance (revenues from taxes including carbon tax and expenditures on government consumption investments, transfers, debt servicing including subsidies to R&D). There is a direct correspondence (one-valued function) between the values of parameters belonging to this class and the corresponding macroeconomic variables such as national accounts, labor data, or public sector accounts. Formally speaking, this means that the steady state of the model (and the long-term growth path – the trend of the baseline scenario) is unambiguously determined by the observed data, and the first class of model parameters is unambiguously determined by them. Parameters belonging to this class take values implied by observations and the structure of the model, and their values are determined by the numerical solver in such a way that the stationary state of the model reflects the most current state of the world economy. These data come directly from the WorldBank, OECD, IMF and Eurostat databases and are publicly available, and the parameters determined on their basis are determined accurately.

The second group of model parameters covers about 15-17% of their total number and almost exclusively elasticity occurring in the functions describing individual segments of the model, like production technologies, labor market parameters, household utility function, etc. These elasticities are responsible for the relative response of individual variables to macroeconomic shocks and, consequently, related to their deviations from the reference variable (e.g. GDP) in the business cycle. They are determined on the basis of World Bank data or calibrated on the basis of the literature on the subject. In the first case, the estimation is made in a similar way as in the model of Smets and Wouters (2007), i.e. using Bayesian estimation methods. They are commonly used in DSGE modelling (cf. An and Schorfheide (2007) and Herbst and Schorfheide (2015)) due to their flexibility and versatility and at the same time impartiality, i.e. resistance to the preferences of the modelling team. These parameters do not depend significantly on a given economy, because they reflect the more universal properties of economic entities: the shape of human preferences, the specificity of global production technologies or the nature of the inventive process. As such, they do not have to or even should not be determined on the basis of national data, but rather be supported by cross-sectional international data or specialized literature on the subject dealing with individual thematic areas, i.e. works whose authors dealt with the parameterization of DSGE models.

At the same time, in the case of some parameters, estimation is unnecessary due to the high consensus in the literature as to the range of variability of given parameters. It may also be impossible due to the lack of relevant data. This applies to about 5% of the model's parameters. In such situations, a given parameter is determined on the basis of a literature review. This applies to the elasticity of substitution between labor and capital, which we assume at level 1 (Cobb-Douglas function). Similarly, the risk aversion parameter as a function of consumption is determined after the literature (cf. Kydland and Prescott (1982) at level 2 ($\sigma = 2$), which is a value used as standard in DSGE models. On the other hand, the consumer's time preference is directly determined by the annual frequency of the model ($\beta = 0.95$ – cf. Smets and Wouters (2007)).

The third class of parameters is the least numerous (3-5% of the total number of parameters) and at the same time depends on the specific research questions posed to the model. As a rule, they can take any values depending on the type of questions they are asked to the model. If, for example, we assume that economic operators treated the intervention under the climate policy as short-lived, the autocorrelations of the respective shocks will be close to zero. If, on the other hand, we find they are – in the expectations of the subjects – permanent, we will give them values close to number one. In both cases, the response of the model in the short term may be different, although in the long run it will be the same. Intermediate values are also possible depending on the simulation needs. The same is true for other shocks.

The numerical solution of the model is a solution of the constituent optimization problems around the baseline scenario including the determination of equilibrium prices in the markets for all products and factors of production simultaneously, which makes it possible to determine the optimal allocation of resources in the economy at any given time. This creates a system of equations that describes the behavior of economic agents (each individually and all together) around the baseline scenario, which takes into account the conditions that constrain their decisions and the conditions of equilibrium (clearing of individual markets). The mechanism represented by the structural form of the model contains the encoded decision rules of economic agents, in the form of a dynamic system that describes the response of the variables that make up the modeled economy in response to the shocks included in the model. In other words, it decodes the decision rules that make up the model records them in an operational form that allows simulations to be performed. Such simulations can, in particular, concern various economic policy tools, including those covered by measures falling under the regional policy intervention for a given economy like the world climate policy coordinated by the UN.

4.4 Results

4.4.1 Analyzed scenarios

The simulations conducted are qualitative in nature. Their purpose is not to precisely represent any of the SSP scenarios, but rather to indicate the potential role of research and development, the dissemination of innovation (imitation), and their interaction with carbon taxes and potential subsidies for companies implementing innovations that lead to emission reductions.

The reference scenario (BAU) was constructed to approximately reflect the SSP-3-6.0 scenario. Therefore, it largely reflects the already visible global trends in economic growth and greenhouse gas emissions, as well as the dissemination of technology. In this scenario,

average global carbon prices remain low until 2080, and technological progress in zero-emission technologies proceeds autonomously (without subsidies). The global adoption of zero-emission technologies is so slow that it cannot outweigh the increase in greenhouse gas emissions implied by global economic growth until around 2060. We compare moderate and ambitious climate policy scenarios implemented in different ways with the reference scenario:

1. The first is the "CO2 large tax small subsidies" scenario, which assumes a focus on rapid emission reduction based on high taxation, without recycling tax revenues for R&D purposes. It is similar to, but not identical to, SSP1-2.6.
2. The second scenario under consideration, "CO2 large tax large subsidies," assumes the same taxes as in the reference scenario, but a decreasing portion of revenues goes to supporting R&D activities and the uptake of low-emission technologies in companies, which implies a different CO2 taxation.
3. The third scenario under consideration, "CO2 BAU tax small subsidies," establishes carbon taxes at a level similar to the SSP 2-4.5 scenario, but with only autonomously set R&D expenditures and permitted imitation. This is therefore a scenario that supports R&D, but does not emphasize increasing economic incentives for implementing innovation through a higher emissions tax and R&D subsidies simultaneously.
4. The fourth scenario under consideration, "CO2 BAU tax large subsidies," is a modification of the previous scenario to include R&D subsidies in a manner analogous to the second scenario. This scenario, therefore, combines R&D support with incentives for implementing zero-emission technologies in the later period.

4.4.2 Carbon tax and Green R&D expenditures

The following pair of charts illustrate the predicted growth paths for emission allowance prices and spending on green innovations in each scenario. Carbon tax rates in the ambitious scenarios exceed \$150 per ton of CO₂ in the second half of the 21st century, before stabilizing or even declining slightly. In the passive scenarios, this level is not reached until 2100, and for most of the period, the CO₂ price is lower (below \$50 or even \$30 per ton). A reverse pattern applies to research and development expenditures, which are high at the beginning of the period (i.e., the 2020s) due to the anticipated increase in emission allowance prices, only to decline decade by decade as demand for new technologies declines, while the pool of available inventions expands, and thus the unit cost of purchased low-carbon capital decreases.

The pattern reproduced by the model is therefore similar to the predictions of Acemoglu et al., 2016, who, based on a deterministic model, indicated that in the face of global warming, the optimal behavior is high upfront R&D expenditures, gradually replaced by an increase in the carbon tax, encouraging companies to implement existing solutions, i.e., invest. At the same time, the model predicts that in scenarios with a higher expected CO₂ price growth path, the response from R&D expenditures will also be stronger, increasing by 0.5%-1% of GDP between 2020 and 2030. In this way, companies seek to protect themselves against the future effects of warming (declining growth and revenues), while at the same time, in scenarios of ambitious climate policy, they benefit from R&D subsidies and investments in zero-emission technologies.



Figure 2: Carbon tax and Green R&D expenditures in different scenarios

4.4.3 CO₂ emissions and impact on green innovations

The second pair of metrics affected by both carbon taxes and green R&D subsidies is greenhouse gas emissions. As illustrated in the chart in the panel below, the model with the assumed tax rates accurately reflects the SSP scenarios of interest (SSP 1-2.6, SSP2-4.5, and SSP3-6.0), yielding similar CO₂ emission projections by 2100. For the purposes of this article, it's particularly noteworthy that the differences between the individual scenarios favour the variants that allow R&D subsidies from funds collected through CO₂ taxes. In these scenarios, at a given level of allowance prices, emissions reduction occurs faster, or—if the reduction occurs at the same rate—the carbon tax rate may be lower. As a result, these scenarios are associated – compared to their counterparts assuming no active support for R&D – with a level of aggregate welfare (measured by the utility stream from consumption discounted by preferences) that is approximately 2%-5%.

Because the model also accounts for the damage caused to the global economy by excessive global warming, companies, anticipating this eventuality, tend to invest more in research upfront than downstream. At the same time, due to the externalities built into the model, a large portion of the benefits from innovation are public in nature (an externality flowing from the pool of accumulated capital), which means that in scenarios with low CO₂ costs, and consequently, with the expected late achievement of reduction targets, the scale of R&D expenditures is low. Companies spend the most on research when CO₂ costs are high and research subsidies are financed from them.

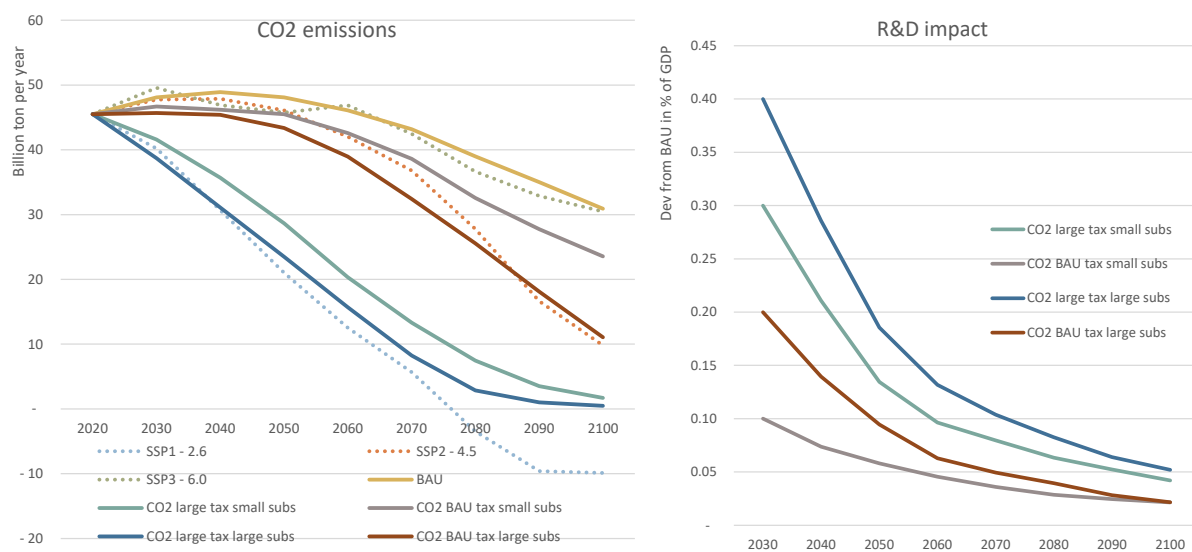


Figure 3: Green R&D expenditures and impact on green innovations in different scenarios

4.4.4 GDP per capita and output gap

The welfare lost due to global warming can be assessed by analysing its impact on GDP. This is illustrated in the graph below, which indicates that the sensitivity of the presented model to climate and CO₂ shocks is lower than that of the IAM models used by the IPCC. This may be because, anticipating the upcoming warming and rising CO₂ costs, agents in the model under consideration also raise prices, reducing, for example, GDP growth relative to the SSP1-2.6 scenario. The gap between the output level in 2100 between the BAU scenario and the most ambitious of the climate scenarios we considered is almost two-fold. On average, this corresponds to a difference in the average annual GDP growth rate of approximately 0.4 percentage points over 80 years. The largest gap in growth rates occurs at the beginning and end of the period, which is related to the fact that, over time, economic agents in the model adapt even to the most strongly correlated shocks, translating into catching up on previously lost ground. Other indicators that are strongly correlated with GDP, such as consumption, employment or capital accumulation, also develop in a similar way, and in the short term the behaviour of these variables is greatly influenced by whether the shock is anticipated or not.

4.5 Conclusions and Policy Implications

This research embeds directed green innovation and carbon pricing in a DSGE framework with search frictions in labor markets, financial frictions, and an explicit climate block. The model highlights a strong complementarity between rising carbon taxes and front-loaded, time-limited R&D support: when firms internalize an anticipated path of higher CO₂ prices, they invest heavily in green knowledge early on, and when those efforts are co-financed from carbon-tax revenues, diffusion and adoption accelerate, allowing a given climate target to be achieved at lower tax levels or, for a given tax, with faster emissions reductions. The optimal temporal pattern mirrors the “invent early–tax later” logic in the directed technical-change literature: high R&D outlays up front that gradually decline, while carbon prices rise and do more of the deployment work later in the transition.

Quantitatively, under ambitious policy paths carbon prices exceed \$150/tCO₂ in the second half of the century, while green R&D rises by ~0.5–1% of GDP in the 2020s, then tapers as the stock of accessible zero-emission technologies expands and unit costs fall. In scenarios that recycle a decreasing share of carbon-tax revenues to R&D and adoption support, welfare (lifetime utility) improves by ~2–5% relative to comparable paths without R&D support, and emissions fall more rapidly at any given price. Conversely, “passive” paths with low taxes and no targeted subsidies postpone innovation, lock in higher near-term emissions, and deliver lower welfare.

Macroeconomic outcomes reflect the interplay between expectations, frictions, and damages. Because agents are forward-looking, the economy reprices sooner in ambitious scenarios—moderating near-term GDP relative to a purely deterministic IAM benchmark but yielding a much higher level by 2100 than in BAU. The model produces an almost two-fold gap in output levels between the most ambitious climate path and BAU by 2100, which corresponds to an average growth-rate difference of roughly 0.4 pp per year over eighty years. These dynamics are consistent with a damage process that hits productivity (a technology shock), together with gradual adaptation of prices, employment, and capital accumulation

Mechanistically, green R&D augments firm-level TFP in the energy-producing KE-bundle, with positive knowledge spillovers that are ignored by individual firms. Carbon pricing shifts relative factor demand away from fossil inputs toward green capital, while spillovers and adoption frictions make the social return to early R&D exceed the private return. Financial frictions and labor-market search costs slow the transition on the margin; monetary policy (via a Taylor rule) shapes nominal adjustment and interacts with “green inflation” pressures, but does not overturn the central complementarity between pricing carbon and subsidizing innovation.



Policy implications are direct:

1. Pair a rising, predictable carbon-price path with front-loaded, declining R&D and adoption support, financed from carbon-tax revenues. This sequencing minimizes transition costs by moving the invention margin early and the deployment margin later.
2. Target externalities: prioritize support where knowledge spillovers and adoption frictions are largest (energy production and energy-using capital), recognizing that private incentives under-provide socially optimal research
3. Coordinate fiscally and internationally to scale public-good knowledge creation while limiting leakage; recycle residual revenues to ease distributional impacts and maintain political support.
4. Alleviate financing and labor frictions (e.g., green-investment credit channels, re-skilling) to reduce transitional output gaps without diluting price signals.

Finally, while the simulations are qualitative and benchmarked to SSP-style trajectories, the main message is robust within this setting: ambitious carbon pricing delivers more, not less, when coupled with targeted, front-loaded support for green R&D and diffusion. This policy mix reduces required tax levels for a given abatement, accelerates emissions decline, raises welfare, and yields substantially higher end-of-century output than business as usual.



5 Improving technical change and innovation aspects in IAMs: Introducing Digital Services in the WITCH Model

5.1 Context and Motivation

The growing integration of digital technologies into economic and societal systems raises critical questions for energy use, productivity, and climate policy. While digitalisation is often linked to efficiency gains and innovation, it also drives a substantial increase in electricity demand. Integrated Assessment Models (IAMs), such as WITCH, must explicitly account for this dual role of digitalisation to accurately capture structural economic transitions and inform sustainable policy design.

This extension of the WITCH model introduces a dedicated digitalisation sector that reflects both the productivity-enhancing effects of digital services and their dependence on electricity use. This allows for a more nuanced analysis of the interactions between digitalisation and energy systems transition.

Digital technologies affect energy systems along two dimensions. First, the operation of these technologies directly consumes electricity—for example, students or workers using AI tools like ChatGPT at home, or industries relying on cloud computing and automation. Second, digitalisation can also contribute to energy efficiency improvements, such as through smart grids, building automation systems, or AI-assisted optimisation in manufacturing. It is therefore crucial to represent both the direct energy demand and the potential energy-saving effects of digitalisation in IAMs.

Empirical evidence highlights these trends related to digitalization: the share of electricity consumption from ICT-related activities is rising globally, with data centres and network infrastructure accounting for an increasing fraction of total electricity demand. Rapid growth in data traffic, cloud services, and AI deployment in industry further reinforces the need to integrate these dynamics into energy and climate modelling frameworks.

Capturing these dynamics in IAMs is critical for designing effective climate strategies and forecasting reliably energy demand dynamics. Understanding the interplay between digitalisation and energy systems can inform policies to mitigate rebound effects, support the development of energy-efficient digital technologies, and guide digital industrial policies towards net-zero goals. This extension provides a foundation for evaluating trade-offs and synergies between digital and green transitions, helping policymakers align innovation strategies with ambitious climate targets.

5.2 Model Implementation

In the enhanced version of the WITCH model, Digital services are modeled as a distinct input into final goods production, reflecting their growing importance in modern economies. They are produced by combining digital capital and electricity. A key mechanism in this formulation is the substitutability between traditional energy services and digital services. Economies that invest in digital capital may improve their productivity, reduce energy intensity, but increase demand for electricity, shifting the energy profile toward electrification.

5.2.1 Final Good Production Function

In the WITCH model, the final good Y is produced using a nested Constant Elasticity of Substitution (CES) function combining capital–labor and digital–energy blocks.

$$Y_t = tfp_0 / \Omega_t [\alpha (tfp_{y_t} K_{FG,t}^\beta L_t^{1-\beta})^\rho + (1 - \alpha)(DS_t^\gamma ES_t^{1-\gamma})^\rho]^{1/\rho} - \sum_f C_{f,t} - \sum_{ghg} C_{ghg,t}$$

where:

- K_{FG}, L, ES represent the capital, labor and energy services used in the final good production;
- DS represents the digital services used in the final good production;
- α is the weight assigned to the nested KL;
- ρ is a parameter governing the elasticity of substitution between the two combination of inputs;
- β and γ are the parameters of the nested cobb douglas functions;

In this production function, each parameter reflects a distinct economic mechanism. The parameter α represents the capital share in the capital–labor bundle; higher values of α indicate a more capital-intensive economy, whereas lower values suggest a greater reliance on labor. The parameter γ governs the contribution of digital services relative to energy services. A high γ means that the production is more digital-intensive, potentially improving energy efficiency through substitution. Finally, σ is the elasticity of substitution between the two composite input blocks: capital–labor and digital–energy services. A higher σ implies greater flexibility for the economy to shift resources between these input combinations in response to technological or policy changes.

By allowing for a degree of substitution between digital services (DS) and energy services (ES), the model captures the potential energy efficiency gains that can arise from the use of digital technologies. At the same time, because the production of DS itself is electricity-intensive, the framework also accounts for the additional energy demand associated with digitalisation.

5.2.2 Digital Services Production

Digital services are generated through a Cobb-Douglas function of digital capital (K_D) and electricity (EL_D):

$$DS_t = [\alpha_D (EL_D)^{\rho_D} + (1 - \alpha_D)K_D^{\rho_D}]^{1/\rho_D},$$

where:

- K_D is the Digital capital;
- EL_D is the Electricity input for digital production;
- α_D is the capital share in digital services.

In the model, digital services (DS) are represented as a heterogeneous set of technologies,

including artificial intelligence (AI), robotics, and additive manufacturing (e.g., 3D printing). The corresponding digital capital stock (K_D) is technology-specific. For instance, in the case of AI, K_D comprises data centres, high-performance computing infrastructure, and algorithmic frameworks, which, together with electricity input, generate digital outputs.

The model's flexible structure enables distinct calibration schemes to assess the contribution of different classes of digital technologies to electricity demand.

Furthermore, the accumulation of digital capital is governed by the standard law of motion:

$$K_{D,t+1} = K_{D,t}(1 - \delta_D)^{\Delta t} + \Delta_t I_{D,t},$$

where δ_D denotes the depreciation rate and $I_{D,t}$ denotes investment in digital capital. Importantly, the depreciation rate of digital capital may differ from that of traditional capital used in the production of final goods, reflecting differences in technological obsolescence and replacement cycles.

5.2.3 Energy Splitting

In the model, total energy demand (EN) is defined as the sum of electricity (EL) and non-electric energy (NEL):

$$EN_t = EL_t + NEL_t$$

A key departure from the benchmark WITCH model is the disaggregation of electricity demand (EL) into two distinct components to account for the growing role of digitalisation in the energy system:

$$EL_t = EL_{DS,t} + EL_{ES,t},$$

where

- EL_{DS} : electricity consumed in the production and operation of digital services, and
- EL_{ES} : electricity used in all other energy services unrelated to digitalisation.

This distinction allows the model to capture the dual role of digital technologies as both consumers of electricity and potential drivers of energy efficiency improvements. Specifically, EL_{DS} reflects the electricity demand from data centres, networks, and end-user devices associated with digital services, while EL_{ES} corresponds to traditional electricity uses in industry, transport, and households as represented in the WITCH modelling framework.

5.3 Preliminary Insights

The calibration of the extended WITCH model is still ongoing, given the limited and heterogeneous empirical evidence on the energy and productivity effects of digitalisation. In this preliminary stage, the focus is placed on one of the most measurable components of digital infrastructure: data centres. Specifically, we examine their impact on electricity demand, based on existing literature that estimates the share of electricity attributable to data centre operations.

In our current calibration, we set the share of electricity demand from data centres at 2% of total electricity consumption. This value reflects the lower-bound estimates found in recent IEA and academic studies and serves as a reference point for the analysis of digitalisation's direct energy footprint (see, e.g., IEA 2025).

The updated model structure enables us to decompose electricity demand into two

components:

- EL_{DS} : electricity consumed by digital services (e.g., data centres)
- EL_{ES} : electricity consumed by the rest of the economy

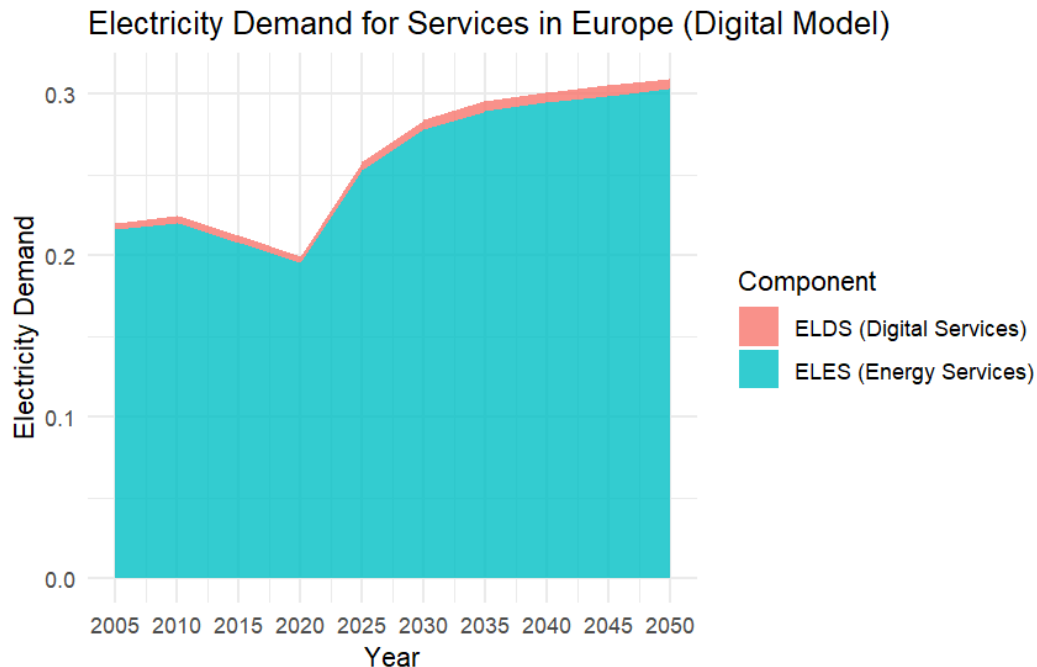


Figure 4: Electricity Demand for Services in Europe (Digital Model)

We present below preliminary results for Europe, covering the time horizon 2005–2050. Figure 4 shows the evolution of total electricity demand in two scenarios: the benchmark model (without digital services) and the digitalisation scenario (with explicitly modelled digital services).

As expected, the inclusion of digital services leads to an increase in electricity demand. This is consistent with empirical trends that highlight the growing energy footprint of data centres and digital infrastructure (e.g., IEA 2025). At the same time, Figure 5 shows that non-electric energy demand (e.g., fossil fuels, bioenergy) declines more rapidly in the digitalisation scenario. This indicates a faster pace of electrification, as digital technologies substitute traditional energy inputs and increase productivity and efficiency in several economic sectors. The results suggest that while digitalisation increases electricity needs, it may also contribute to a structural shift in the EU's energy mix, with potential implications for decarbonisation strategies.

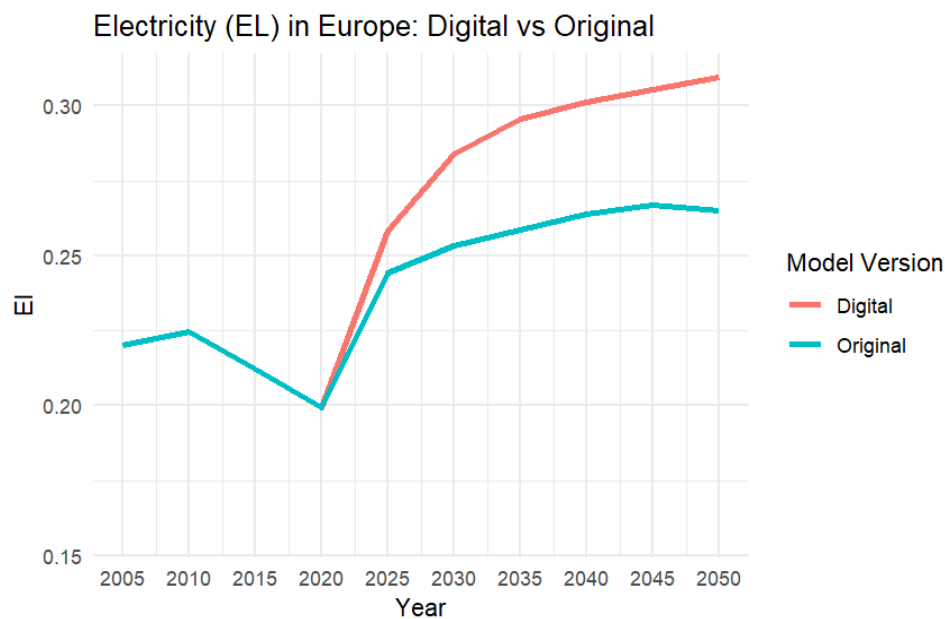


Figure 5: Electricity in Europe: Digital vs Original

These initial results underscore the importance of explicitly modelling digitalisation in IAMs. Even a narrow focus on data centres reveals a non-negligible impact on energy demand and electrification dynamics. Future work will broaden the scope to include other digital technologies and assess their implications for productivity and emissions.

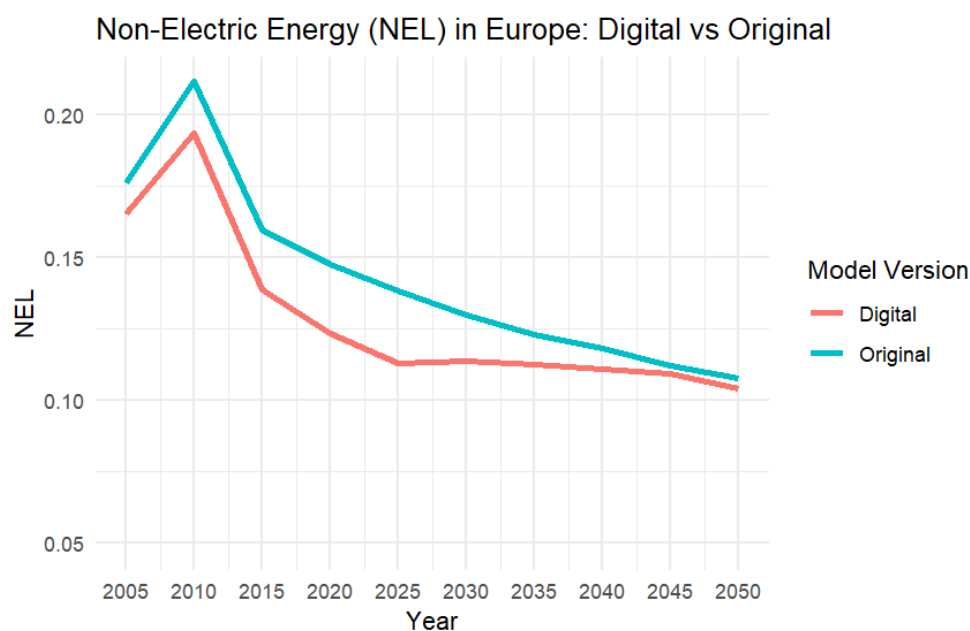


Figure 6: Non-Electric Energy in Europe: Digital vs Original

5.4 Next Steps

The next phase of this research will focus on consolidating and further improving the model structure and expanding its analytical scope. A key priority is the empirical calibration of substitution elasticities and productivity parameters associated with digital services, drawing

on data sources classified under ISIC 6311 (Data Processing, Hosting, and Related Activities) to characterise digital capital intensity and electricity consumption. Building on this, the WITCH model will explore alternative diffusion scenarios of digital technologies across regions to assess their implications for total electricity demand, aggregate productivity growth, and emissions trajectories.

An important extension is the integration of labor market dynamics to capture the interactions between digitalisation and labor, with particular attention to how different types of technologies affect the demand for high- and low-skilled workers. This addition will enable the analysis of employment and distributional impacts and potential complementarities or substitution effects between digital capital and various labor categories.

Finally, the WITCH model will be used to study the feedback mechanisms between digitalisation, emissions, and climate policy, investigating potential rebound effects, synergies with energy efficiency, and implications for long-term decarbonisation strategies. These developments aim to provide a more comprehensive and reliable framework for assessing the role of digitalisation in shaping energy and climate futures.



6 Representing dynamic and heterogeneous Cost of Capital in the IMAGE model

6.1 Motivation and Objective

Deep decarbonization across all sectors is essential to meet the Paris Agreement targets, yet many integrated assessment models (IAMs) assume uniform financing conditions, ignoring country-, technology- and sector-specific investment risks. This simplification can bias mitigation pathways and underestimate mitigation costs, particularly in developing countries where the cost of capital (CoC) is significantly higher. The objective of this study is to quantify the impact of differentiated CoC on global mitigation strategies by incorporating dynamic, region- and sector-specific financing conditions into the IMAGE IAM, covering nine energy and industry sectors beyond electricity generation.

6.2 Methodology

The study first derives empirical CoC estimates for each sector and region by combining sovereign risk premiums (based on credit ratings) with sector-specific risk measures from financial market data. A detailed description of the method to derive these CoC can be found in the PRISMA Deliverable D3.1. These estimates are aggregated to IMAGE model regions using GDP-weighted averages and adjusted for corporate tax rates. To capture future dynamics, we model the relationship between economic development and country risk. This approach introduces a feedback mechanism between economic growth and investment risk, improving realism compared to static financial assumptions.

The differentiated CoC values are implemented in the IMAGE IAM, which simulates energy and industry system transitions under two scenarios: (i) current policies and (ii) a mitigation pathway consistent with keeping global warming well below 2 °C. The analysis isolates the effects of CoC differentiation on technology choices, energy prices, and emissions, both with and without endogenous climate policy adjustments to maintain the climate target.

6.3 Preliminary results

Accounting for heterogeneous financing conditions increases cumulative global mitigation costs. Higher CoC in developing countries shifts investments away from capital-intensive options such as renewables, grids, and electrolysis-based hydrogen, favoring fossil-based technologies and delaying electrification. Industrial sectors like cement and steel exhibit slower uptake of carbon capture and low-carbon processes, while hydrogen costs rise significantly in high-risk regions. These findings highlight that ignoring financing heterogeneity might lead to overly optimistic assessments of global decarbonization feasibility.

7 Improving technical change and innovation aspects in IAMs: Exploring technology-specific spillovers in IMAGE

Incorporating technological innovation through learning curves in integrated assessment models (IAMs) is essential for accurately projecting the future cost and adoption trajectories of clean energy technologies, which in turn shape global and regional mitigation pathways. As research on innovation and technological change has evolved, modelers increasingly endogenize learning processes—linking unit cost reductions directly to technology deployment and thereby capturing cost feedback dynamics within the model structure.

Within PRISMA, some IAMs represent technological learning endogenously through learning curves, while others rely on exogenous cost projections derived from empirical studies. Among the models that endogenize learning (such as IMAGE), many assume that technologies learn globally, using spillover matrices to represent the cross-regional diffusion of innovation through deployment. In the context of IMAGE, spillovers describe how the deployment of a technology in one region positively (or negatively) influences its deployment in other regions. However, the empirical and theoretical basis for calibrating these spillover values remains limited.

This exploratory modeling exercise investigates how modifying the structure of these knowledge flows—by adjusting the spillover matrix according to emerging theoretical insights (see below)—affects clean technology adoption and, by extension, global emissions trajectories within the IAM IMAGE.

7.1 Theoretical Framing and Research Plan

Technological learning can occur at both global and local levels. Existing theory suggests that the extent to which a technology learns globally versus locally depends largely on the degree of customization required for its deployment environment. Technologies that must be tailored to local regulatory, infrastructural, or geographic conditions tend to exhibit more localized learning dynamics, whereas modular, standardized technologies display more globalized learning behavior.

For instance, nuclear power plants are highly customized systems that must be adapted to country-specific regulations and site-specific constraints. As a result, they are characterized by high design complexity, limited opportunities for replication, and in some cases even negative learning rates (e.g. increasing nuclear costs after the Fukushima accident). By contrast, solar photovoltaics (PV)—a modular and standardized technology—require minimal local adaptation and have exhibited consistently high empirical learning rates across regions.

From this perspective, we hypothesize that technologies with high customization requirements exhibit predominantly *local learning*, meaning that cost reductions from deployment in one region do not fully translate to cost reductions in other regions. Conversely, technologies with low customization needs tend to benefit more from *global learning*, where knowledge and experience gained in one region spill over more readily to others. Understanding which energy technologies learn “globally” versus “locally” is therefore essential for accurately modeling innovation diffusion and technology cost dynamics.

The objective of this exploratory analysis is to operationalize these theoretical insights

within the IAM IMAGE framework. Specifically, we aim to adjust the so-called “spillover matrices” to reflect varying degrees of knowledge transfer across regions and assess the implications for technology adoption and emissions trajectories. The research plan involves:

- Preliminary testing with regional spillover rates for selected technologies under two contrasting assumptions:
 1. A *global learning* scenario, where knowledge diffuses freely across regions.
 2. A *differentiated local learning* scenario, where knowledge transfer is more constrained.

The goal of this first exercise is to understand the dynamics of the model and to have a benchmark estimate of the maximum effect of global learning in addition to local learning.
- Exploring a set of hypothetical geopolitical “worlds” to capture the influence of international trade and cooperation on learning dynamics:
 1. *Perfectly open trade* – a harmonized, globally integrated system.
 2. *Completely closed trade* – a world of regional isolation and limited knowledge exchange.
 3. *Intermediate trade openness* – a balanced world reflecting partial regional integration.

7.2 Preliminary Testing

In the current implementation of the IAM IMAGE, technology spillover matrices typically assume a uniform spillover rate of 90% between model regions. In practice, this means that 90% of the deployment experience of technology α in region A is assumed to spill over to region B, and vice versa—implying a highly integrated global learning process for all energy technologies.

To explore the sensitivity of results to this assumption, we conducted a set of preliminary tests focusing on solar PV as a representative globally diffused technology. For this purpose, we compared two contrasting configurations:

1. Default spillovers (90%) – representing the standard IMAGE assumption of near-complete global learning.
2. No spillovers (0%) – representing a fully localized learning regime, where deployment experience remains confined to individual regions.

These two configurations were evaluated under the SSP2 baseline scenario both with and without climate policy constraints.

Preliminary findings indicate that the assumption about cross-regional spillovers can have a substantial effect on the modeled unit cost of solar PV—particularly in the USA region (see Figure 7). In the absence of spillovers, the regional learning process slows markedly, leading to higher projected costs for PV compared to the default case with 90% spillovers. The modelled capital cost projections show to be more sensitive to these spillover assumptions compared to the sensitivity to the introduction of the carbon price in the mitigation scenario.

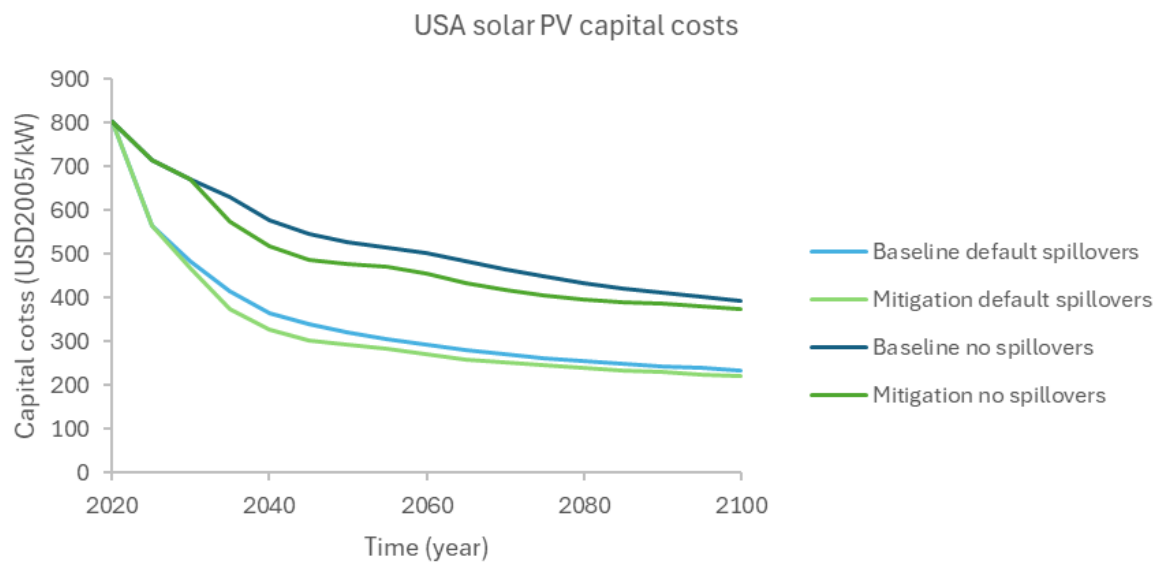


Figure 7: Capital costs with and without intra-regional learning spillovers. Example: PV costs in the US.

8 Projecting regional techno-economic costs under socio-economic development pathways

Authors: Measrainsey Meng, Paul Kishimoto, Oliver Fricko, Volker Krey

A key factor in mitigating climate change is the deployment of low-carbon technologies, and as a result, the evolution of technology costs into the future will have significant impact on climate-related policy measures. Integrated Assessment Models (IAMs) and Energy Systems Models (ESMs) are widely used to support climate and energy policy, and their projections depend significantly on the assumptions made about technological costs and performance. However, these models often require a large number of input assumptions, and applying a consistent method to project costs for all technologies can be challenging. We present an open-source Python-based tool to exogenously project investment and fixed operational & maintenance costs of energy technologies with regional specificity across scenarios. The tool offers a standardized, modular approach that simplifies the input process and promotes the reproducibility of cost projections within models, providing a valuable resource for more transparent model design. By providing a consistent method for cost projection, it helps to address some of the challenges of applying diverse assumptions across different technologies within models. We demonstrate its application within the MESSAGEix IAM framework by projecting costs for energy technologies under the Shared Socioeconomic Pathways (SSP) SSP2 scenario. This tool can also be adapted for use in other models, as well as applications for technologies in non-energy sectors such as the chemical industry.

8.1 Introduction

Understanding how the costs of energy demand and energy supply technologies change over time is of key importance for analysts and decision-makers concerned with technology development, the evolution of national and global energy systems, and the implications of policy measures proposed to address global climate change or other energy-related issues. Low-carbon technologies in the energy system have been identified as a key element for mitigating climate change. The relative importance of mitigation technologies depends on their techno-economic characteristics and how they develop in the future (Intergovernmental Panel On Climate Change (IPCC) 2023a; Bosetti et al. 2015). The trajectories of techno-economic characteristics are dependent on several interconnected mechanisms, such as market demand, knowledge spillovers, low-carbon innovation, and technological learning (Nemet 2006; Wiesenthal et al.)

Energy systems models (ESMs) and Integrated assessment models (IAMs) of climate change, which combine dynamic descriptions of the energy-economy system, the climate system, and climate impacts, have been increasingly used to inform energy and climate policy. IAMs utilize a wide range of assumptions and inputs for techno-economic parameters, and the results of the IAMs are heavily impacted by the representation and parameterization of technologies within these models (Intergovernmental Panel On Climate Change (IPCC) 2023b). A number of studies have found that assumptions for the future of certain technologies such as carbon dioxide removal, bioenergy coupled with carbon capture and storage, and nuclear power plants can have significant impacts on the emissions and policy costs outputs of IAMs (Bosetti et al. 2015; Kriegler et al. 2014; Riahi et al. 2015). A comparison of technological assumptions across fifteen IAMs found that there are large differences in both the structural

representation and numerical parameterization of energy-related technologies between IAMs (Krey et al. 2019). Table A.1 in the appendix shows a selected number of IAMs and how technological change is implemented in each respective model. For most models, techno-economic cost assumptions are exogenous inputs. Some models implement endogenous technological change for a subset of technologies, often variable renewable energy technologies. However, also in these models, many technologies and processes still rely on exogenous cost assumptions.

Techno-economic parameters may vary significantly across regions. As global IAMs are often used to model different energy and climate futures, the costs of technologies will also vary greatly depending on the assumptions and constraints of different scenarios.

One of the most often utilized approaches to projecting technology costs is a model-based approach, which uses observed data on one or more variables to approximate future costs. A commonly used model to forecast technological changes is the learning curve (or experience curve). Derived from Wright's law, this approach postulates that a doubling of capacity (or production) of a certain technology leads to a reduction in cost by a fixed percentage called the "learning rate" (Wright 1936). Another commonly used method is based instead on a "progress rate" (derived from Moore's law), which postulates that the costs of a technology decrease exponentially over time (Moore 1998).

Model-based approaches have been applied to project technology costs numerous times in the literature. The largest number of learning rates studies for a single energy technology are for onshore wind and solar photovoltaics (PV). Studies have also been conducted focusing on the costs of more mature fossil fuel electricity generation technologies, such as coal (Rubin et al. 2007; Li et al. 2012) and natural gas (Rubin et al. 2007; Van Den Broek et al. 2009) power plants. Other studies presented reviews of technology cost projections for a range of energy technologies (Rubin et al. 2015; Schmidt et al. 2019; Weiss et al. 2010; Malhotra and Schmidt 2020).

Given the large suite of technologies modelled in IAMs, a significant number of inputs, assumptions, and data are required to project technology costs. Additionally, it is difficult to consistently apply a standard method of cost projections across all technologies, possibly leading to inconsistencies in the projections. Finally, often the cost projection methods are not clear or transparent, leading to concerns for the reproducibility of cost assumptions and further adding to the difficulty of updating cost assumptions at a later time. Thus, while there is no right or wrong from an ex-ante perspective, making the techno-economic projections transparent, reproducible and allowing for sensitivity analysis in a structured way is an important step forward.

We present an open-source tool to exogenously project technology costs (capital costs and fixed Operation & Maintenance - O&M) with regional specificity across scenarios. This tool allows for a modular, standardized approach to projecting costs for a large number of technologies to be used in ESMs and IAMs. To simplify the problem of large data input requirements, we use defined data sets plus a limited set of assumptions on cost reductions, fixed O&M cost ratios, and choice of convergence algorithm as input to the tool.

This tool has been developed for use in the MESSAGEix IAM framework in the PRISMA project, but it is also configurable to be used in other modelling applications by allowing to export datasets using the standardized scenario data template developed by the Integrated

Assessment Modeling Consortium (IAMC)⁵. This study demonstrates the application of the tool for energy technologies, but similarly the tool's inputs can be modified to project costs for technologies in other sectors (e.g., chemical or steel industry). We apply the tool to a use case where we project costs under the Shared Socioeconomic Pathways (SSP) SSP2 scenario.

8.2 Methods

Figure 8 provides an overview of the inputs and processes in the costs projection tool.

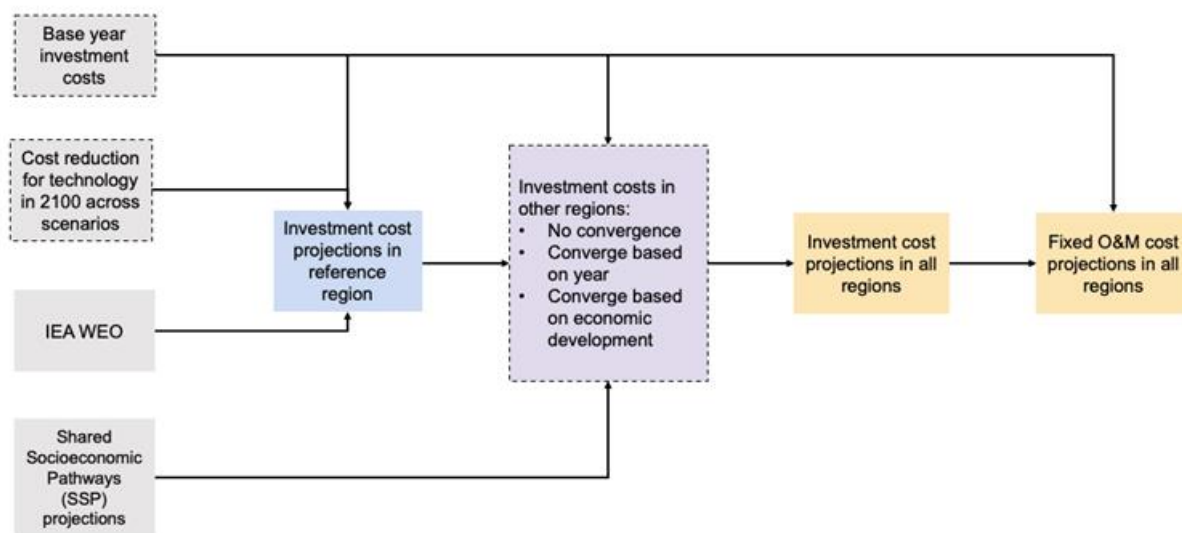


Figure 8: Overview of the cost projection tool's processes.

8.2.1 Reference region

In this tool, we assume that one region is defined as the “reference region” that leads the development of a technology with all other regions following the cost of the reference region. The reference region can be selected by the user. To regionally differentiate costs in the base year, we apply a cost value assumption in the base year for a technology in the reference region. This value can be supplied for each technology as an input by the user, but if no base year cost is supplied for a technology, then a cost value from the International Energy Agency's (IEA) World Energy Outlook (WEO) dataset is used (IEA 2023).

To regionally differentiate costs for a technology in the base year, we utilize the IEA WEO 2023 dataset. We use the mapped WEO technology's costs across regions in 2022 to derive cost ratios relative to the reference region. These regional cost ratios are applied to the reference region's base year cost to quantify base year costs in all regions.

To project costs, a cost “reduction rate” is applied: the cost from the base year exponentially decays until the cost reaches the reduced cost fraction (relative to the base year cost) specified in the year 2100. The reduction rate is supplied as a user-input and can vary for each individual technology and scenario.

⁵ <https://github.com/IAMconsortium/common-definitions>

8.2.2 Projection of costs across regions

The exponential decay of cost from the base year until 2100 is first applied to the reference region. After the costs in the reference region are projected, it is then possible to project costs in all other (non-reference) regions. The tool allows for three possible methods to project these costs, (i) no convergence, (ii) converge to reference region by year, and (iii) converge to reference region based on GDP per capita which we explain in the following.

Method 1: No convergence

In the “No convergence” method, we assume costs across all regions do not converge. The regional cost ratios derived in the base year for a technology are applied to the projected reference region’s costs until the year 2100.

Method 2: Converge to reference region by year

The second method assumes that all regions’ costs converge to the reference region by a certain year, which can be supplied by the user. All costs in the non-reference regions linearly approach and reach the reference region’s projected costs by the convergence year.

Method 3: Converge to reference region based on GDP per capita

In this method, we assume that GDP per capita can be used as an indicator of technology costs. Instead of converging all regions’ costs to the reference region based on a specified year, we postulate that convergence happens based on GDP per capita: as region x’s GDP per capita grows closer to the reference region’s GDP per capita, so does region x’s technology costs. To do this, we derive projected regional cost differentiation ratios after the base year to the year 2100 by developing a linear relationship between the regional investment cost ratio to the regional GDP per capita ratio for each technology. Using the projected GDP per capita ratio from the SSPs, we can derive regional investment cost ratios into the future for each technology. These regional investment cost ratios are then applied to the reference region’s projected investment costs.

8.2.3 Projection of fixed O&M costs

Fixed O&M costs are projected as a constant fraction of investment costs (thus following the same trajectories as the investment costs). Users of the tool can specify technology-specific ratios of fixed O&M cost to investment cost. If a ratio is not provided by the user, the tool will use the fixed O&M cost and investment cost in 2022 from the mapped IEA WEO technology. The ratio is kept constant throughout the projected time horizon.

8.2.4 Output

The projection tool is able to produce the output of the cost projections data in two formats: (1) a format that is compatible for input into MESSAGEix and (2) a format that standardized by the Integrated Assessment Model Consortium (IAMC), which would allow the data to be used by others, even for non-modelling specific purposes.

8.3 Use case: MESSAGEix and SSP2

In this study, we showcase an application of the costs tool for the MESSAGEix integrated assessment model. Specifically, we use a 12-region (R12⁶) resolution of the global model.

⁶ <https://docs.messageix.org/projects/models/en/latest/pkg-data/node.html#region-aggregation-r12>

MESSAGEix uses the investment costs of all technologies to build out energy capacities. The fixed O&M costs describe how much operation and maintenance of the technology that do not depend on the level of operation cost.

We provide a use case of the costs projection tool applied to the SSP2 scenario. The SSP2 scenario is the “Middle of the road” scenario amongst the SSPs, with the assumption that there will be medium challenges to climate change mitigation and adaptation. In general, the global social, economic, and technological trends do not diverge significantly from historical trends and patterns under the SSP2 scenario.

8.3.1 Data sources

The tool uses existing energy technologies cost data from the IEA’s World Energy Outlook (IEA 2023) to regionally differentiate technology costs. Within the tool’s inputs, each modelled technology is mapped to a corresponding IEA WEO technology, to allow for the regional cost differentiation (detailed further below). Additionally, each region used in the model is mapped to a WEO region. Country-level gross domestic product (GDP) and population projections from the Shared Socio-economic Pathways⁷ are utilized for the cost projections (KC et al. 2024). The country-level data are aggregated to the regional level.

8.3.2 User-specified inputs

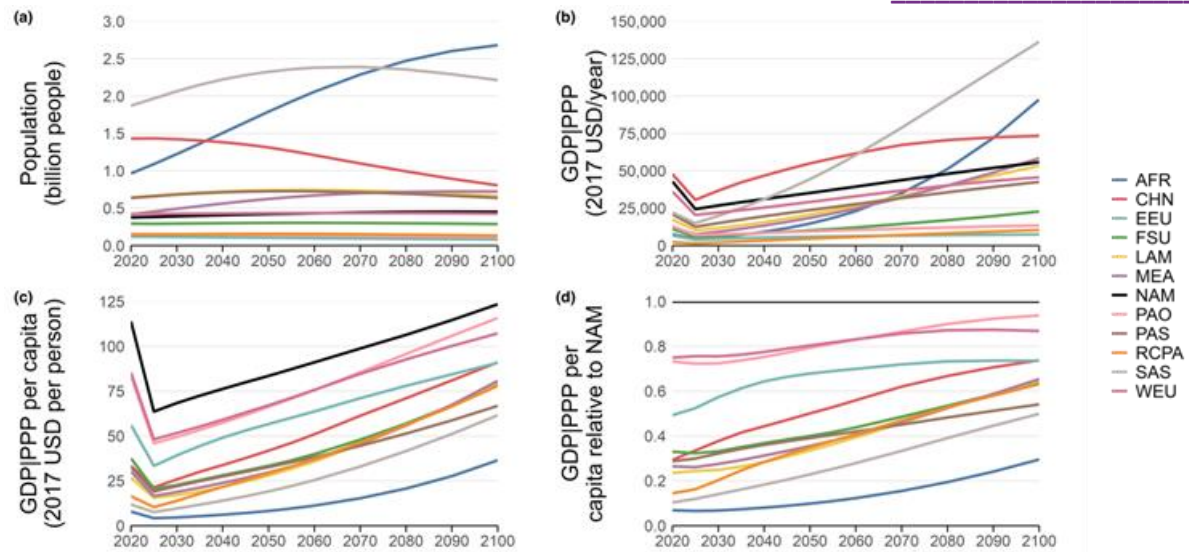
To project the costs for a technology, the following information can be supplied as inputs by the user:

- WEO mapped technology: each modelled technology is mapped to a technology in the IEA WEO technology, whose costs are meant to be similar to the modelled technology
- Base year cost: the cost of the technology in the base year; if none is provided, then the mapped technology’s cost in 2022 from the IEA WEO is used
- First year: the first year the technology is deployed (if later than the base year, e.g., in the cases of CCS technologies)
- Cost reduction in 2100 across scenarios: the assumed reduction in the technology’s cost (in percentage terms) in 2100 compared to the base year
- Fixed O&M cost percentage: the ratio of fixed O&M cost to investment cost; if none is provided, then values from the mapped IEA WEO dataset technology are used

8.4 Results/Discussion

Figure 9 shows the population (panel a) and GDP projections (panel b) in the SSP2 scenario aggregated to the 12 regions of the MESSAGEix model. Figure 9 (c) shows the GDP per capita calculations for the regions while panel (c) displays the calculated GDP per capita ratio, using North America as the reference region. The ratios for all other regions are projected to move towards 1.0 over time, indicating that in the SSP2 scenario, all other regions’ GDP per capita will gradually converge towards North America’s.

⁷ SSP 3.1 release: <https://data.ece.iiasa.ac.at/ssp/>



[VK1]

Figure 9: Projections shown for R12 regions under SSP2. (a) Population in billions of people. (b) Gross domestic product (GDP) purchasing power parity (PPP). (c) GDP/PPP per capita. (d) Regional GDP/PPP per capita, relative to using NAM as a reference region.

Figure 10 shows the base year investment costs for a select number of technologies modelled within MESSAGEix, again using North America as the reference region. The cost differentiation between North America and the other regions are based on the IEA WEO's 2022 costs values. The tool can capture the large cost differences across regions, especially for certain technologies such as nuclear, biomass, and wind, where the costs to install a power plant for these fuel types can vary greatly depending on the geographical location.

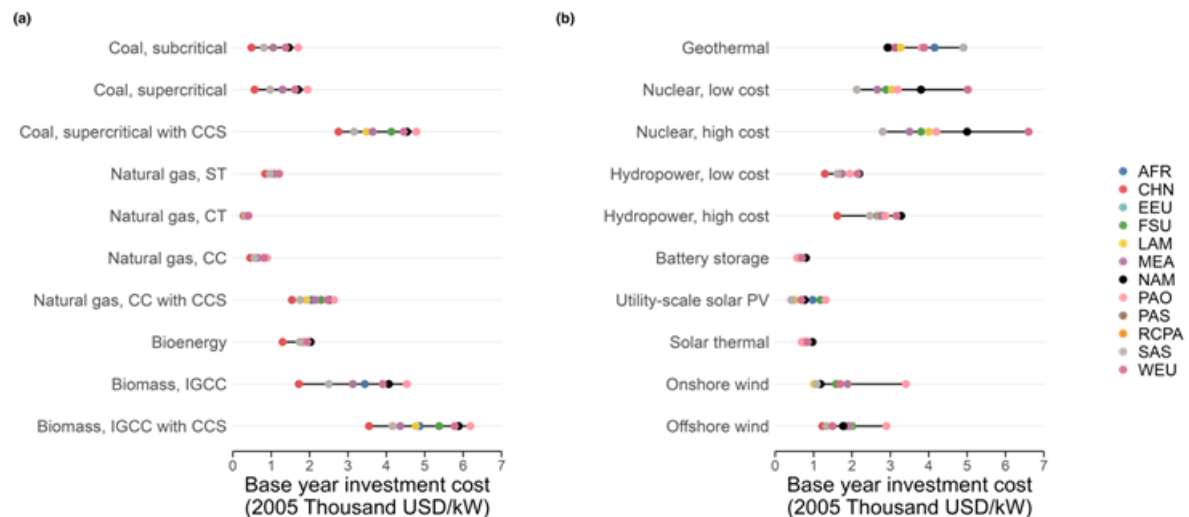


Figure 10: Investment costs in base year for a select number of (a) fossil fuel technologies and (b) renewable technologies.

Figure 11 shows the resulting outputs of the tool: cost projections for technologies over the time horizon for each region. In the figure, the differences in cost projections across the three regional differentiation methods can be seen clearly. The regional

costs based on the static cost ratios method all follow an exponential decay. The costs that converge based on a year all meet at North America's cost projections, as that is specified as the reference region. The GDP per capita-based convergence shows the greatest variety in projection dynamics across regions, as these cost projections are dependent on projections of GDP and population for these regions.

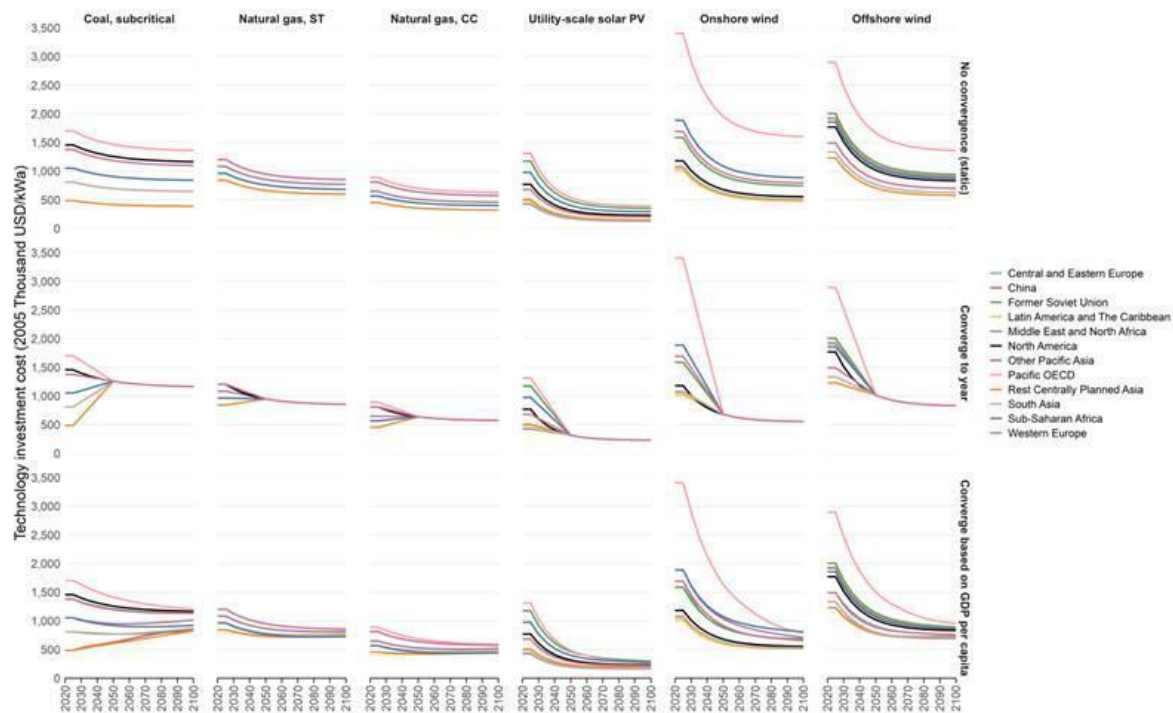


Figure 11: Cost projections of selected energy technologies using the three methods. Results shown use North America as the reference region. Note that the base year in these projections is 2025, as such the costs from 2020 to 2025 are kept constant. The converge to year method assumes a convergence year of 2050.

The outputs from the cost tool can be used as inputs into MESSAGEix (or any other IAM). Figure 12 and Figure 13 show the results of applying the different cost projections in MESSAGEix (using the different regional differentiation methods). The electricity supply technologies displayed are coal, gas, solar PV, and wind power plants. Installations and utilization of technologies are dependent on the investment costs of the full suite of technologies available in a model, as cheaper technologies are selected to be deployed. While we only focus our examples on these four technologies, it is important to note that the deployment of these technologies is also greatly affected by the cost projections of all other “competing” technologies not shown here. The installed capacity of a technology is influenced by the investment cost (as well as other considerations such as resource availability, legal constraints, permitting, etc). In Figure 12, for coal capacity, we can see that coal capacity in China is so prominent that coal capacity in all other regions is very small in comparison. For natural gas capacity, the cumulative capacity increases across regions up until approximately 2050, where the cumulative capacity mostly remains stagnant globally. Solar PV and wind cumulative capacity grow massively across all regions until the end of the century. Considering that by mid-century solar PV is projected to become cheaper than coal and natural gas plants (Figure 10), the capacity results shown accordingly follow the cost projections.

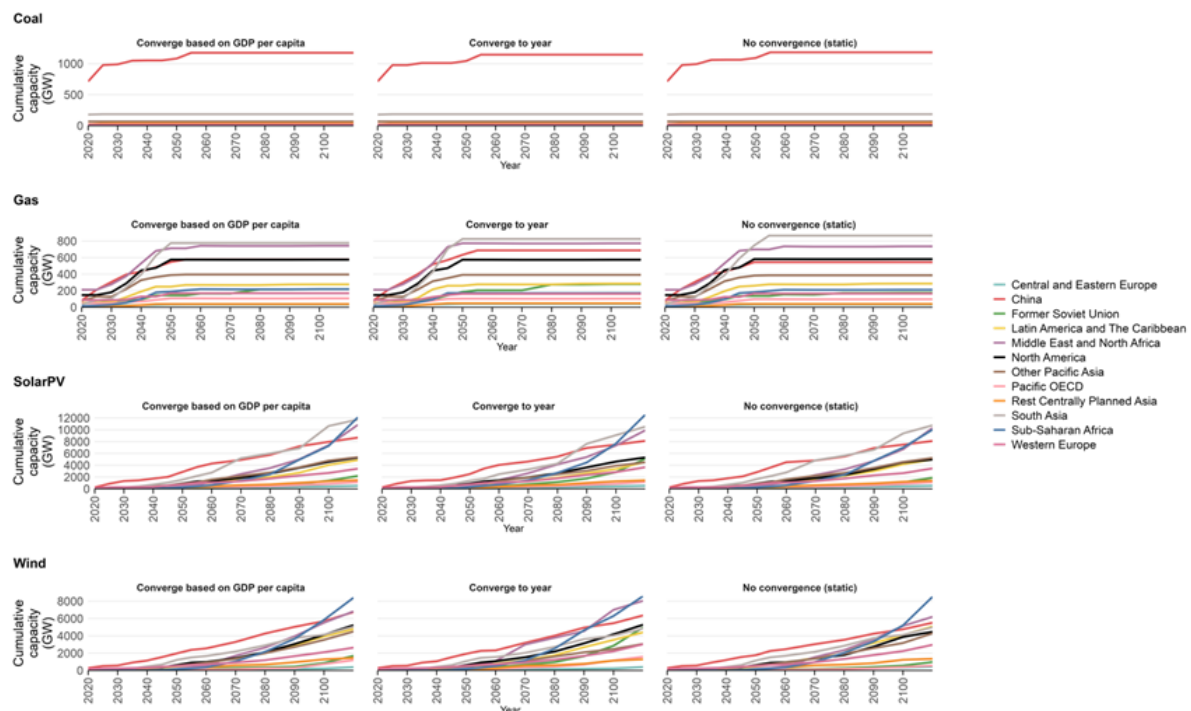


Figure 12: Cumulative capacity installed for select energy technologies (coal, natural gas, solar PV, and wind) in a 2°C compatible scenario with cumulative CO₂ emissions of 1000 Gt from 2020 until 2100.

The electricity generated from a technology is dependent on the fixed O&M costs (along with other factors such as fuel costs, variable costs, carbon costs, regulations, etc). In the case of solar PV and wind power plants, the electricity generation trends fairly closely follow the trends of cumulative capacity, which is likely because the tool's fixed O&M costs projections follow the same trends as the investment costs. However, the results for electricity generation vary significantly from the cumulative capacity results for coal and natural gas. In the case of coal and natural gas power plants, we are likely seeing the impact of a carbon budget taking precedence and forcing the phase out of coal and natural gas from the power mix.

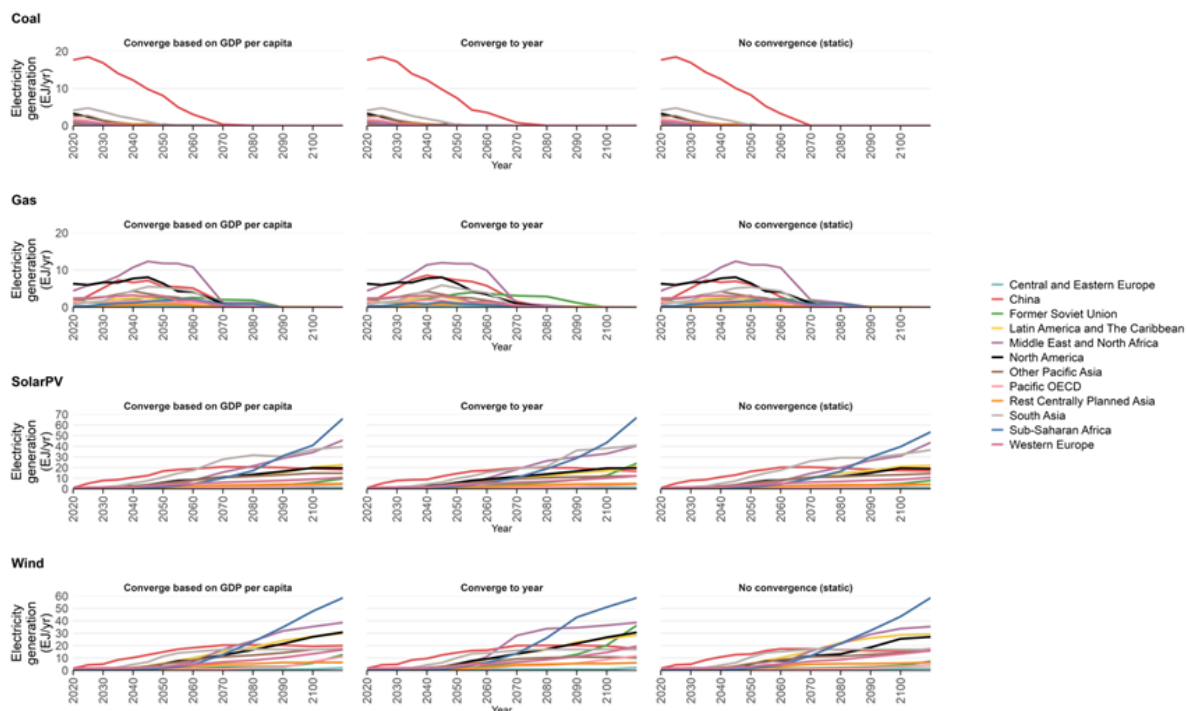


Figure 13: Electricity generation for selected energy technologies (coal, natural gas, solar PV, and wind) in a 2°C compatible scenario with cumulative CO₂ emissions of 1000 Gt until 2100

8.5 Model sensitivities

The cost projections are heavily dependent on several data inputs and assumptions. First, because the base year cost is the starting point for all technologies, the assumed cost will greatly affect the projected costs for the time horizon. Second, the selection of the reference region will also have a large impact on the cost projections for all regions, as the base year cost is assumed to be in the reference region. Thus, depending on the reference region selected, the regional differentiation can be completely altered, as the investment cost ratios and GDP per capita ratios are all relative to the reference region. The technology mapping also has an impact on the projection of costs. While we mapped each MESSAGEix energy supply technology to an IEA WEO technology to the best of our abilities, we recognize that some technologies do not map as well as others. This same issue applies for the region mapping from R12 regions to IEA countries, where we best tried to select the IEA country that would likely drive the cost in an R12 region. Finally, the assumption of cost reduction rates for each technology in the scenario will have a significant effect on the model deployment of technologies. Because a model such as MESSAGEix looks at the costs of the full suite of technologies, how the costs for all technologies change over time relative to one another is important, not just the cost of an individual technology.

Limitations

In building standardized, consistent cost projections for a significant number of technologies, there are a few limitations and simplifications that exist within the tool. The first limitation is that the tool is currently only able to represent the change of costs over time as an exponential decay, which is not reflective of all technologies. One of the future work planned

for this tool is to allow for the projection of costs using different curve types. Second, the GDP per capita method relies on the assumption that a lower GDP coincides with lower costs. However, some regions such as PAO (Pacific OECD) and WEU (Western Europe) are in unique instances where they have a lower GDP per capita than North America but higher technology costs. If the GDP per capita ratio of PAO or WEU relative to NAM increases over time, this could cause costs to increase instead within the tool. We have prevented this issue by not allowing the cost ratio to move “backwards” (decrease from the base year cost ratio).

8.6 Usage of the tool

Although the use-case application presented in this paper is for a 12-region version of the MESSAGEix model, the tool can be configured and applied to different spatial resolutions and for usage in different integrated assessment models.

The tool introduced in this paper provides technology-specific investment and fixed O&M cost projections over time, with spatial granularity, across different scenarios. By simplifying and reducing the number of assumptions and inputs needed, this tool is lightweight enough to quickly produce cost projections for a large suite of technologies, which is needed for integrated assessment models. Additionally, through the application of the projection methods, cost projections for all technologies will be consistent. The tool has been configured to be modular to easily allow for the addition of technologies and scenarios. Finally, the tool addresses a need for transparent and open-source cost projections methods within the IAM community.

The cost projection tool is released open-source under an Apache 2.0 license, which allows for both the usage of the tool by the broader community and the receipt of feedback for continued improvement and modifications of the tool. Code data and documentation of the tool are available under the following URLs:

- GitHub repository: <https://github.com/iiasa/message-ix-models>
- Documentation: <https://docs.messageix.org/projects/models/en/latest/api/tools-costs.html>

8.7 Appendix

Table A.1: List of integrated assessment models and their respective implementations of technological change (Krey et al. 2019)

Model	Technological change			
	Agriculture	Energy conversion	Energy end-use	Material use
AIM-Hub	Exogenous	Exogenous	Exogenous	Exogenous
BET	No	Exogenous	Exogenous	
BLUES	Endogenous	Endogenous	Endogenous	Endogenous
C3IAM	Endogenous	No	Exogenous	No
COFFEE-TEA	Endogenous	Endogenous	Endogenous	Endogenous
DART		Exogenous	Exogenous	
E3ME-FTT		Endogenous	Endogenous	

ENV-Linkages	Exogenous	Exogenous	Exogenous	Exogenous
EPPA	Exogenous	Exogenous	Exogenous	
Euro-Calliope		Exogenous	Endogenous	
GCAM	Exogenous	Exogenous	Exogenous	Exogenous
GEM-E3		Endogenous	Exogenous	Exogenous
GENeSYS-MOD		Exogenous	Exogenous	
GMM		Exogenous	Exogenous	
GRACE	Exogenous	Exogenous	Exogenous	
ICES	Exogenous	Exogenous	Exogenous	Exogenous
IMACLIM		Endogenous	Endogenous	
IMAGE	Exogenous		Endogenous	Exogenous
IPAC-Global	Exogenous	Exogenous	Exogenous	Exogenous
MEDEAS		Endogenous	Endogenous	Endogenous
MERGE-ETL		Endogenous	Endogenous	
MESSAGE-GLOBIOM		Exogenous	Exogenous	
MUSE	Endogenous	Endogenous	Endogenous	No
POLES		Exogenous	Endogenous	
PRIMES	Exogenous	Exogenous	Endogenous	
PROMETHEUS		Endogenous	Endogenous	
REMIND-MAgPIE		Endogenous	Endogenous	
REMod		Endogenous	Endogenous	
SNOW GL HH	Endogenous	Endogenous	Endogenous	Endogenous
TIAM-ECN	Endogenous	Endogenous	Endogenous	
TIAM-UCL		Exogenous	Exogenous	
VESPA	Endogenous	Endogenous	Endogenous	Endogenous
WEGDYN	No	Exogenous	Exogenous	Exogenous
WITCH	Exogenous		Endogenous	
WITNESS	Endogenous	Endogenous	Endogenous	Endogenous



9 International Knowledge Spillovers in Energy Technologies

This study has been published in the Energy Strategy Reviews journal, as “Kim, Y.J. and Verdolini, E. (2023). International knowledge spillovers in energy technologies. Energy Strategy Reviews, 49, 101151. <https://doi.org/10.1016/j.esr.2023.101151>”

9.1 Research Context and Methodology

This study by Kim and Verdolini (2023) examines international knowledge spillovers in energy technologies across 29 countries from 1990 to 2015, with particular focus on comparing mature renewable energy technologies (wind and solar PV) with efficient fossil-based generation technologies. The research addresses a critical gap in understanding how knowledge flows across borders in the energy sector, which is essential for achieving decarbonization targets and informing climate mitigation efforts.

The analysis employs patent citation data as a proxy for knowledge flows, building on established methodologies from Peri (2009) and Verdolini and Galeotti (2011). The study examines multiple barriers to knowledge diffusion including geographical distance, linguistic differences, trade barriers, technological distance, and environmental policy distance. The sample period is divided into two sub-periods (1990-2002 and 2003-2015) to capture temporal dynamics, with the split motivated by the adoption of the EU Emissions Trading System Directive in 2003.

The econometric approach uses a negative binomial model to account for the count data nature of patent citations. Seven key barriers to knowledge diffusion are tested: crossing country borders, geographical distance, linguistic barriers, trade barriers, technological distance between countries, distance in technological development levels, and environmental policy stringency distance. The analysis generates knowledge spillover matrices that quantify the probability of knowledge flowing from one country to another, relative to domestic knowledge flows, which can be directly incorporated into integrated assessment models and macroeconomic models.

9.2 Main Findings on Knowledge Spillover Patterns

The research reveals striking differences in knowledge spillover patterns between mature renewable and fossil-based technologies, with important temporal dynamics. For the full sample period, crossing a country border reduces citation likelihood to 29% for mature renewables and 31% for fossil-based technologies compared to domestic patents. However, the evolution of these patterns diverges significantly between the two technology types.

Temporal dynamics show opposite trends: International knowledge spillovers increased substantially in intensity for wind and solar technologies in the period 2003-2015 compared to 1990-2002, while the opposite is true for fossil-based technologies. This finding suggests that foreign knowledge has increasingly informed domestic innovation in low-carbon technologies, pointing to the critical role of international knowledge flows in promoting renewable energy innovation and contributing to the rapid cost reductions observed in wind and solar technologies over the past two decades.

Geographical and linguistic barriers matter differently: Geographical distance hinders knowledge flows for both technology types, but its role changes over time. For mature

renewables, geographical distance was a more significant barrier in 1990-2002 than in subsequent years, suggesting improved international collaboration and knowledge transmission mechanisms. Linguistic barriers significantly reduce knowledge flows only for fossil-based technologies (reducing citation probability to 76% between countries without common languages), while mature renewable energy knowledge flows more easily across linguistic borders.

Technological distance is increasingly important for renewables: Knowledge flows are higher between countries with similar technological profiles, but this effect is more pronounced for mature renewable technologies. The role of technological distance increased over time for wind and solar: in 1990-2002, citations between countries with completely different renewable innovation profiles were 45% as likely as between identical countries, but this dropped to 23% in 2003-2015. This suggests that as renewable energy technologies mature, specialized technological capabilities become more important for absorbing foreign knowledge.

Trade and policy barriers show limited impact: Contrary to earlier findings from the trade literature, trade barriers do not significantly hinder knowledge flows in either technology type during the study period, likely reflecting the substantial decline in trade barriers between 2000 and 2014 in the context of increasing trade liberalisation. Environmental policy distance does not emerge as a significant barrier to knowledge flows over the full period, though weak evidence suggests it may have mattered in the early period for mature renewables.

Country-specific patterns: The top innovating countries (Germany, Switzerland, and the US) account for 63% of mature renewable patents and 70% of fossil-based patents in the first period, dropping to 53% and 64% respectively in the second period. This indicates some diversification of innovation activities, with countries like South Korea, Denmark, and China emerging as more significant players in renewable energy innovation in the later period. Figure 14 shows four heat maps showing the estimated knowledge diffusion parameters (Φ) between all country pairs in the sample.

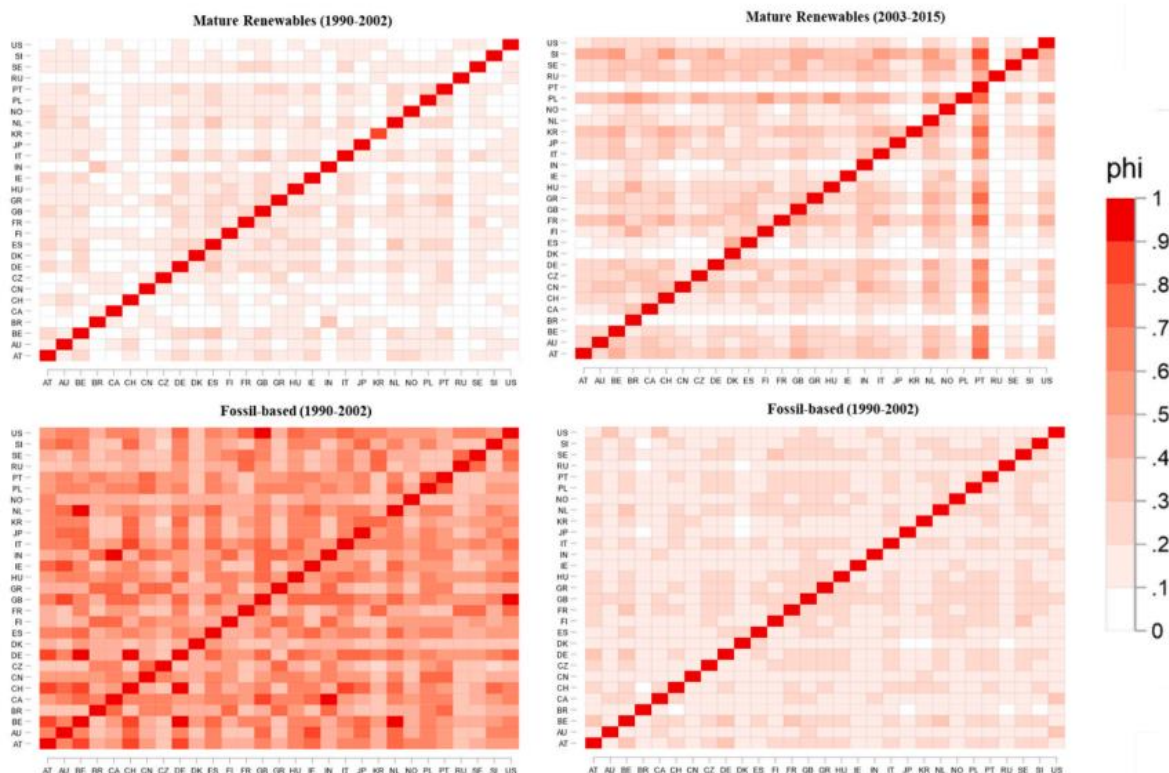


Figure 14: Heat Maps of Knowledge Diffusion Parameters for Mature Renewables and Fossil-Based Technologies (1990-2002 vs 2003-2015)

9.3 Implications for Climate Policy and Modeling

The findings have significant implications for both climate policy design and the calibration of integrated assessment models. The study demonstrates that international knowledge spillovers are technology-specific, time-varying, and should not be treated as static or uniform across different energy technologies.

For integrated assessment models: The study provides empirically-derived knowledge spillover matrices that can be used to calibrate knowledge production functions in IAMs. Current models may underestimate the speed at which renewable energy technology costs decrease by overlooking the intensifying international knowledge spillovers in these technologies. Conversely, models may overestimate the costs of stringent climate policy compliance by underestimating the extent to which countries can build on foreign knowledge to innovate domestically. The contrasting patterns between renewable and fossil-based technologies highlight the need for technology-specific parameterization rather than assuming uniform spillover rates across all energy technologies.

For innovation policy: The increasing importance of technological proximity for accessing renewable energy knowledge suggests that countries need to develop absorptive capacity in specific technology areas. This has implications for technology transfer mechanisms and capacity-building initiatives in developing countries, indicating that successful technology adoption requires not just access to foreign knowledge but also domestic technological capabilities in related areas. The finding that linguistic barriers are less important for

renewables than for fossil-based technologies suggests that renewable energy innovation may benefit from more globalized knowledge networks.

For international cooperation: The substantial increase in international knowledge spillovers for renewable energy technologies demonstrates the public good nature of innovation in low-carbon technologies. This strengthens the case for international cooperation on climate technology research and development, as domestic innovation efforts generate positive externalities for other countries. The relatively small group of frontier countries that dominate innovation suggests potential benefits from targeted international R&D collaborations to accelerate knowledge generation and diffusion.



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11 Appendix

The appendix consists of the published papers related to Section 3 and Section 9.



Macro-financial transition risks along mitigation pathways: evidence from a hybrid agent-based integrated assessment model*

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Abstract

Although the case for a swift climate transition is clear, its macro-financial viability remains uncertain. To shed light on the macroeconomic and financial response to deep mitigation trajectories controlled by carbon pricing, we soft-link a process-based integrated assessment model (the World Induced Technical Change Hybrid, WITCH) to a macro-financial agent-based model (the Dystopian Schumpeter Meeting Keynes, DSK). The hybrid framework allows us to translate energy systems transformations into macro-financial outcomes at business cycle frequency. The results reveal that rapid transitions induced by fast-growing carbon prices significantly impact unemployment, inflation, and income distribution. Stabilization policies reduce these economic fluctuations, though not completely so in 1.5°C-compatible scenarios. Our paper emphasizes the need for coordinated climate and macroeconomic policy during decarbonization. Additionally, it showcases how model integration can lead to a better understanding of the economic implications of low-carbon futures.

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As countries commit to decarbonisation plans, questions around implementation and robust policy design grow in importance. The current consensus is that the world possesses the technology and economic capacity to switch to low-carbon options in many sectors (IPCC, 2022). However, much less is understood about the macroeconomic and financial repercussions of climate neutrality goals at the shorter time-scales of interest to policy-makers (Battiston et al., 2021; Semieniuk et al., 2021). This is a major shortcoming of existing model-based assessments, given the importance of macroeconomic conditions for the political and public support of climate policies (Douenne and Fabre, 2022) and for effective policy design aimed at smoothing the transition and making it inclusive.

The major causes of this limited capacity are methodological and disciplinary boundaries. Model-based assessments of decarbonization policies - especially those performed at the community science level - have focused on technological and sectoral strategies as the main outcome variables. Models supporting these assessments, including detailed-process Integrated Assessment Models (IAMs) (Weyant, 2017), typically feature a stylised representation of economic and financial dynamics (Sanders et al., 2022). Though some have quantified the implications of decarbonization for dimensions such as competitiveness, trade, and sectoral employment, many scenarios only use changes in real GDP, typically at very low temporal frequency, to capture transition costs. Short-run dynamics and impacts on unemployment, balance sheets and the financial system, or inflation are typically not represented. Indeed, none of these macro-financial dimensions is reported in the 1,100 scenarios assessed in the Intergovernmental Panel on Climate Change’s Sixth Assessment Report. Moreover, fiscal or monetary policy responses to macroeconomic impacts induced by climate policy are not typically considered in ex-ante policy assessment. At the same time, such information is highly sought after by finance ministries and international organizations (e.g. the Network for Greening the Financial System, NGFS), and transition scenarios and their implications are becoming increasingly relevant for private financial sector agents (NGFS, 2023; TCFD, 2023).

On the other side, different macroeconomic models have been extended to accommodate energy and climate dimensions, providing insights into the effects of monetary and fiscal policy for the low-carbon transition, and on the repercussions of moving away from fossil-fuel energy for the macroeconomy. These models include extensions of the dynamic stochastic general equilibrium framework (DSGE; e.g. Annicchiarico and Di Dio, 2015; Diluiso et al., 2020; Carattini et al., 2023; Comerford and Spiganti, 2023), post-keynesian ecological macroeconomic models (e.g. Dafermos et al., 2018; Monasterolo and Raberto, 2019; Mercure et al., 2018; Semieniuk et al., 2022), macroeconomic agent-based models (MABM; e.g. Lamperti et al., 2018; Wieners et al., 2024; Turco et al., 2023; Núñez-Yebra et al., 2024; Foramitti et al., 2021), non-linear behavioural macroeconomic frameworks (e.g. Campiglio et al., 2024) as well as network models (e.g. Gualdi and Mandel, 2019; Stangl et al., 2024; Cahen-Fourot et al., 2021). However, the majority of these approaches lacks detailed transition dynamics, such as those depicted by process-based IAMs and included in IPCC mitigation pathways. Indeed, they typically feature only a “green” and a “brown” sector.

This gap presents an opportunity for fruitful cross-fertilization between modelling methodologies providing diverse yet complementary views on decarbonization dynamics. In this paper, we provide - to the best of our knowledge - the first coupling of a macroeconomic agent-based model (DSK¹) and a process-based IAM (WITCH²). Specifically, we establish a one-way link in which WITCH generates the carbon tax trajectories and transition pathways that are subsequently fed into DSK.

¹“Dystopian Schumpeter Meeting Keynes”, which belongs to the “Keynes + Schumpeter” family of MABMs (see Dosi et al., 2010, 2013, 2017).

²“World Induced Technical Change Hybrid” (see Bosetti et al., 2006; Emmerling et al., 2016; Drouet et al., 2021).

This soft link allows us to combine the strengths of both approaches. Macroeconomic agent-based models offer comprehensive frameworks that integrate both long-term and short-term economic dynamics (Fagiolo and Roventini, 2017; Dawid and Delli Gatti, 2018), encompassing real-financial interactions (Delli Gatti et al., 2010) and balance sheet relationships among economic agents (Caiani et al., 2016). In principle, they enable the assessment of transition and climate costs at business cycle frequency, while also capturing growth implications and financial risks (Castro et al., 2020). Additionally, they report on a richer set of micro and macro variables than many other macroeconomic models (e.g. DSGEs), including unemployment, inflation, and distributional variables. Complementary, IAMs offer a fine-grained depiction of decarbonization pathways, including the transformation of the energy and other emitting sectors, their mitigation costs, the investment requirements and the energy mix of the economy accounting for all major energy technologies.

Our modelling approach is the first comparable alternative to NGFS-based scenarios (Richters et al., 2022), which currently form the basis of most climate risk macro-financial analyses relevant to policymakers (Darracq Pariès et al., 2023; Gambhir et al., 2022; Kotz et al., 2024). Our proposed methodology complements existing NGFS approaches by introducing (i) full open access to data and code, (ii) disequilibrium dynamic adjustments, and (iii) energy-finance integration. These enhancements offer novel and highly relevant policy analyses to a wide range of policymakers, such as ministries of finance, central bankers, and financial regulators.

Expanding on established research, our contribution builds upon the solid foundation of soft-coupled models developed in the mitigation literature, where they have been employed to investigate R&D investment strategies for decarbonization (Aleluia Reis et al., 2023), climate-induced financial instability (Battiston et al., 2017; Roncoroni et al., 2021), macroeconomic effects of climate shocks (Yilmaz et al., 2023), housing renovation decisions (Niamir et al., 2024), and provide stronger micro-foundations to otherwise standard Computable General Equilibrium (CGE) models (Niamir et al., 2020). Focusing on transition risks, Allen et al. (2020) and Vermeulen et al. (2018) feed NGFS scenarios defined as carbon price and productivity shocks into a multi-country New Keynesian macro model (NiGEM), which is then linked to sectoral and financial models to perform stress tests. Closer to our approach is the contribution of Catalano et al. (2025), who feed NGFS scenarios into a macroeconomic ABM calibrated for the Italian economy and endowed with a relatively simple energy sector. By comparison to the existing literature, our IAM-MABM approach offers several advantages by (i) incorporating disequilibrium adjustments, which highlight a greater need for stabilization policies and enhanced policy coordination; (ii) enabling the analysis of transition scenarios across more dimensions than those covered by NGFS; (iii) capturing energy sector imbalances more effectively, such as asset stranding due to over-capacity; (iv) providing a comprehensive understanding of energy sector disruptions within a fully-fledged macroeconomic framework.

We use the WITCH model to generate detailed transition pathways. This process-based integrated assessment model combines an inter-temporal Ramsey-type growth framework with a bottom-up representation of the energy sector. The model divides the world into 17 global regions, each playing a non-cooperative game to maximize welfare in response to climate policies. A key decision in this process is how to allocate R&D investments, which can be directed toward improving energy efficiency or developing carbon-free technologies.

The transition pathways produced by WITCH are then aggregated at the global level and fed into the DSK agent-based model, which depicts a single, aggregated economy representing the whole world. The DSK model depicts out-of-equilibrium economic dynamics, capturing both short-run fluctuations

and long-run growth (Lamperti et al., 2018, 2019, 2021; Reissl et al., 2024). It includes seven types of agents interacting across five markets (see Figure 1). Key variables from the WITCH-generated transition scenarios serve as inputs for the DSK model (see Figure 1), allowing for an assessment of the macroeconomic implications of these transition pathways. We should point out that this soft-coupling approach necessarily treats some inputs as exogenous relative to the DSK—most notably policy variables. We return to this point in the Results Discussion Sections, where we explain how our design mitigates this limitation and allows for a quasi-endogenous treatment of the carbon tax.

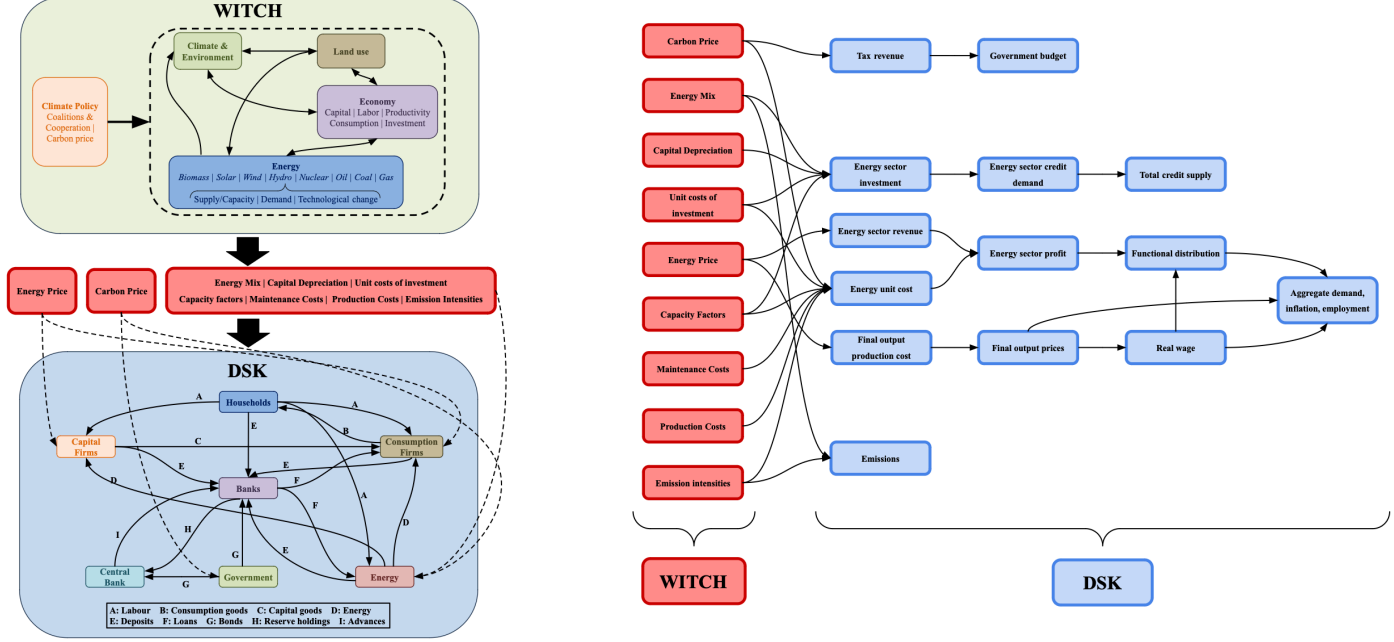
In this paper, we show that an *orderly*, i.e. low unemployment, and *just*, i.e., distributionally balanced, transition are mutually dependent, as the unemployment resulting from aggressive carbon pricing is influenced by how the tax burden is distributed between profit and wage incomes.³ Furthermore, the unequal impact of the carbon tax on the energy sector presents a serious source of instability. While the carbon tax promotes profitability in renewable energy sectors, offering financial support for the transition, it simultaneously undermines profitability in fossil fuel-based sectors, rendering them more susceptible to bankruptcy. Government can mitigate these dynamics by using carbon tax revenues to manage aggregate demand. Redistributing revenues to wage earners can address distributional effects and limit negative macroeconomic impacts, compensating for wage losses and sustaining aggregate demand. We also find that the energy transition will require substantial credit provision for the build-up of renewable energy capacity and that fossil-intensive energy sectors will experience reduced profitability due to carbon pricing and the maintenance of costly stranded assets.

Our results contribute to the literature assessing the macroeconomic impacts of climate policies, regarding regressive effects of carbon pricing (Fremstad and Paul, 2019; Callan et al., 2009; Jiang and Shao, 2014; Farrell, 2017; Känzig, 2023) and the emergence of stranded assets (van der Ploeg and Rezai, 2020; Cahen-Fourot et al., 2021; Semieniuk et al., 2021, 2022). Empirical evidence regarding the macroeconomic effects of carbon pricing is somewhat mixed, with some studies finding no or even small positive effects on GDP (Metcalf, 2019; Metcalf and Stock, 2023) and others predicting negative impacts in the short run (Känzig, 2023). Model-based analyses often predict that aggressive carbon pricing may reduce GDP and employment, but highlight that appropriate revenue recycling can mitigate these outcomes (Brenner et al., 2007; Conefrey et al., 2013; Allan et al., 2014; Rivera et al., 2016; Vermeulen et al., 2018; Allen et al., 2020; Wieners et al., 2024; Rizzati et al., 2025; Konc et al., 2022). Further, they suggest that coordinating climate, monetary and prudential policy can help smooth transition risks, though the desirable mix of such instruments strongly depends on how emission intensive sectors transform (Annicchiarico et al., 2021; Diluiso et al., 2020; Lamperti et al., 2019, 2021). This calls for a more fine-grained modelling of the energy sector, at the very least. Since the carbon price trajectories we examine manifest in relatively sudden increases in the price of energy, our work also contributes to the macroeconomic literature on energy price shocks (Wildauer et al., 2023; Turco et al., 2023; Bodenstein et al., 2008; Auclert et al., 2023; Känzig, 2021). Finally, we contribute to the literature on MABMs (Fagiolo and Roventini, 2017; Dawid and Delli Gatti, 2018) and in particular to two sub-strands. The first regards the analysis of issues related to the green transition (e.g. Safarzyńska and van den Bergh, 2017; Ponta et al., 2018; Hötte, 2020; Rengs et al., 2020) and energy price shocks (van der Hoog and Deissenberg, 2011; Turco et al., 2023; Kremer et al.,

³Here we use a loose definition of orderly and just transition. In our setting, an orderly transition is characterized by low unemployment levels, as a proxy for contained macroeconomic imbalances; a just transition is characterized by a relatively high and stable share of labour income, as a proxy for contained socio-economic inequality. See Newell and Mulvaney (2013) and Wang and Lo (2021) for additional discussion.

2024). The second sub-strand regards the assessment of the macroeconomic consequences of changes in the distribution of income (e.g. Dosi et al., 2018; Caiani et al., 2019; Terranova and Turco, 2022; Fierro et al., 2023).

Figure 1: Overview of the sectoral structure and inter-sectoral interactions depicted by DSK, the structure of the WITCH model, the list of variables from WITCH scenarios used as exogenous inputs, and their main transmission channels to DSK outputs.



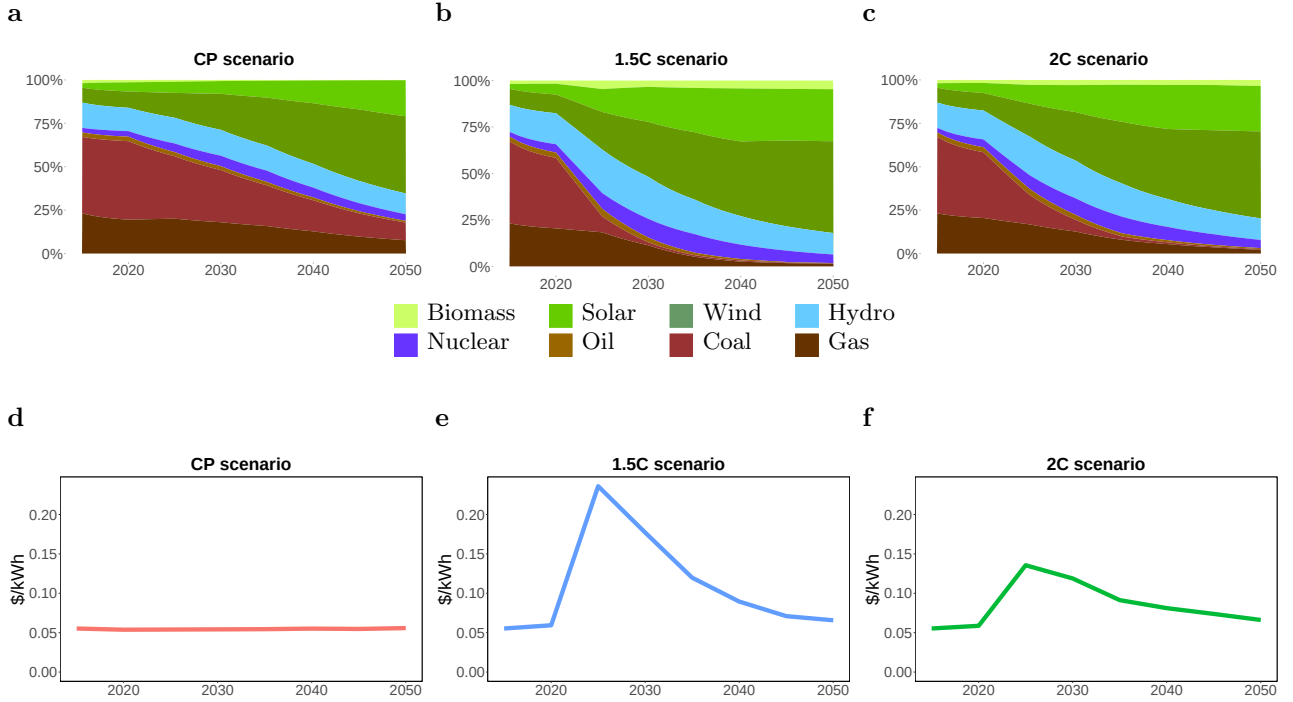
Results

Macro-financial impacts of the transition

We analyze three climate transition scenarios. The “Current Policy” (CP) scenario incorporates policies implemented by 2020 and serves as a baseline. The other two scenarios are designed to limit temperature increases to specific values by imposing carbon budgets from 2020 onward. One features a carbon budget of 1000 GtCO₂, leading to a 2°C temperature increase (2°C), and the other a carbon budget of 500 GtCO₂, leading to a 1.5°C temperature increase (1.5°C). In both cases, carbon budgets are met by imposing a global carbon tax⁴, which we assume countries fully comply with for simplicity, while acknowledging that in reality political deviations from global climate agreements may occur. Another simplifying assumption is that we do not include climate–economy feedbacks in the form of climate-related shocks. This choice allows us to clearly isolate the effects of the carbon tax on the economy, which is the primary mechanism of interest in our analysis. Regarding the DSK policy setting, we initially assume that carbon tax revenues are entirely retained by the government and that the central bank adopts a single-mandate Taylor rule, i.e. it adjusts the interest rate to stabilise inflation (section 1.1.6 in SI); these assumptions will be relaxed in the policy experiments.

⁴The carbon tax is introduced gradually in a standard Hotelling fashion within the WITCH intertemporal optimization framework: the tax is introduced in 2025 and grows at the Ramsey growth rate (around 3-4 percent and declining over time) until globally, net zero emissions are reached, after which it stays at the level required to keep global emissions at net-zero. Its initial value is chosen to meet the carbon budgets set. The initial hike in energy prices is therefore needed to induce a strong shift in the energy system to achieve the carbon budget, and the reduction over time is due to technical progress, notably in renewables, making it cheaper in the long run due to lower installation costs.

Figure 2: Energy price and transition dynamics. **a-c**, energy mix, defined as the share of total energy produced by each technology, for the three WITCH scenarios. **d-f**, energy price in (2005) dollars per kilowatt-hour in the three WITCH scenarios. X-axes always refer to years.



For the sake of clarity, let us stress that the carbon tax designed within WITCH is endogenous to the decarbonization pathway undertaken by the energy sector. By feeding key energy variables—such as emission intensities and the energy mix—into the ABM, we ensure that the energy sector dynamics in DSK remain consistent with the carbon tax at every point in time. Moreover, our fiscal and monetary policy experiments reinforce this consistency by making the broader policy mix explicitly endogenous to the macroeconomic dynamics unfolding in DSK during the transition.

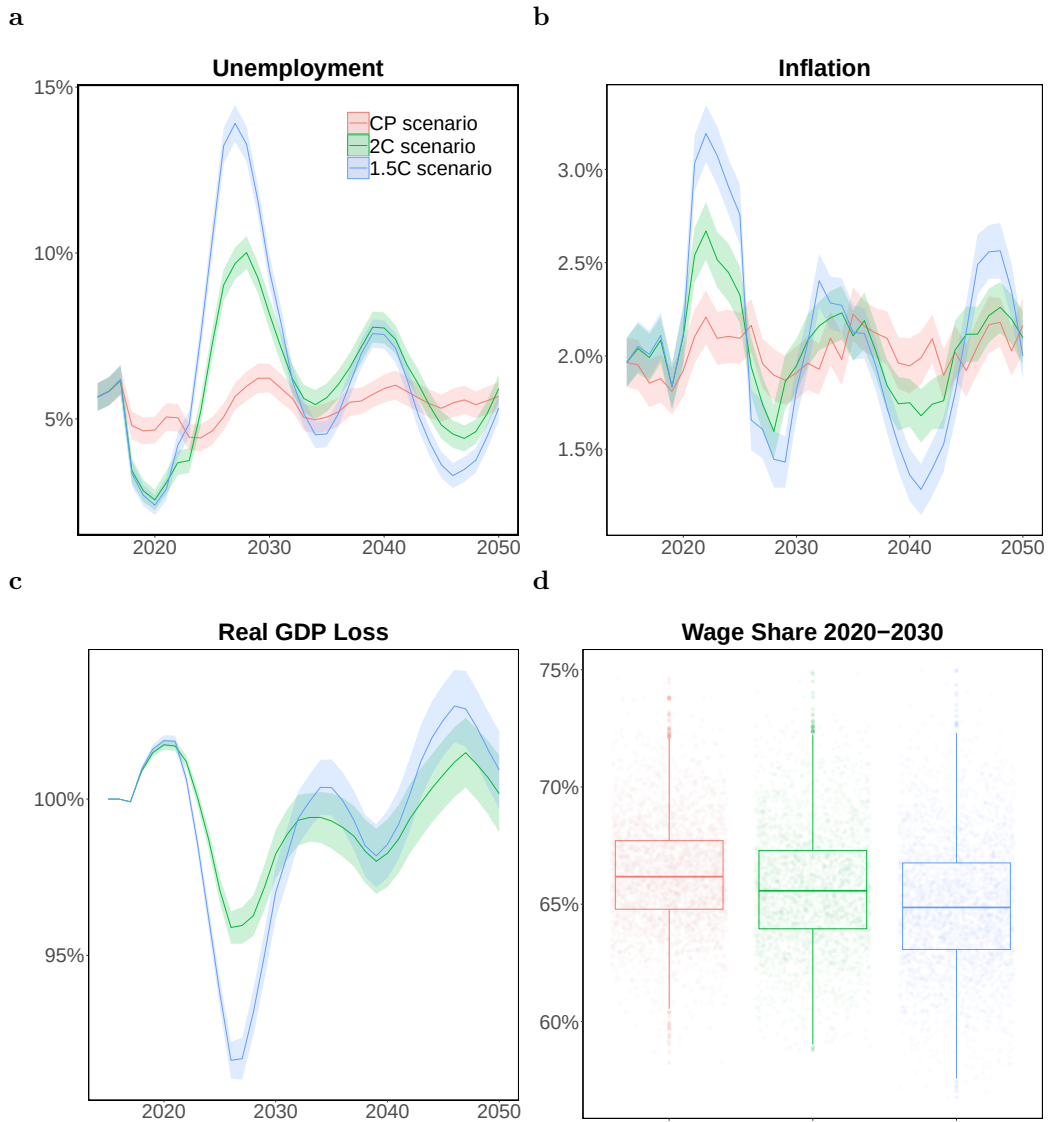
Figure 2 shows the energy mix and price dynamics for each transition scenario. Keeping temperature in line with the goals of the Paris Agreement purely through a carbon price leads to a temporary but sharp increase in energy prices. This is especially the case for the most stringent climate target of 1.5°C where fossil fuels are phased out rapidly during this decade (Figure 2, panel e). In WITCH, the energy system can include the carbon capture and storage associated with oil, gas, and biomass technologies. As targets become more stringent, carbon capture and storage is introduced to reduce unabated emissions and to balance residual emissions.

The energy price shock induced by climate policy leads to a series of macroeconomic adjustments and fluctuations that emerge from the properties of DSK. Figure 3 illustrates these adjustments by comparing scenarios. The main macroeconomic outcome is that of temporary stagflation (Figures 3a-3c) and low wage shares (Figure 3d). Unemployment and low economic growth emerge during this decade in the Paris-compliant scenarios;⁵ the negative impacts on the real economy are accompanied by periods of high inflation.

Figure 4 delves into the mechanisms underlying the dynamics depicted in Figure 3. We find that a key role is played by the wage share, which significantly declines during the early phase of the

⁵Note that before 2020 in both the 1.5°C and 2C scenarios we observe a period of economic boom characterized by falling unemployment and high GDP. This occurs because, in WITCH, economic agents anticipate the future introduction of the carbon tax and begin investing in green energy technology. This investment stimulates economic activity before the carbon tax is implemented, resulting in a brief positive economic cycle.

Figure 3: Macroeconomic dynamics induced by different mitigation pathways. **a-c**, each line represents averages across 300 simulations, shaded areas are 95% confidence intervals, each colour is associated with a scenario; **c**, GDP loss relative to the CP scenario obtained using the ratio between real GDP in the 2C and 1.5°C scenarios relative to real GDP in the CP scenario; **d**, box-plot showing the distributions of wage shares in 300 simulations for of each scenario, period 2020-2030;



transition when energy prices are high. Moreover, its dynamics closely mirror the unemployment rate (Figure 4a). By pooling all simulations across the three scenarios and calculating the quasi-elasticities of unemployment and the wage share with respect to the energy price, we find that high energy prices are associated with high unemployment and a low wage share (Figures 4c and 4d).

Largely unchanged aggregate markups (assumed in the DSK model) imply that carbon pricing and energy price shocks shift aggregate income from labour to the government (via carbon tax revenue) and the "green" energy sectors, while firms' income share remains unchanged. This also triggers a shift from labour income to dividend income, which is disproportionately saved rather than spent (Kaldor, 1955; Bhaduri and Marglin, 1990; Dynan et al., 2004; Dutt, 2017). The final effect is a lack of aggregate demand, leading to low employment and output.

As a result of cost pass-through,⁶ an energy price surge induced by a rise in carbon prices is always inflationary on impact. In addition, nominal wage growth is pegged to the inflation rate (Equation 2 in SI). Higher inflation increases unit labour cost, which in turn feeds back into the general price level. However, wages also respond to labour market conditions, growing slower (faster) when unemployment is high (low). During a stagflationary period, inflation dynamics are hence dampened by weak labour market outcomes.

Figure 4b shows that inflation increases together with the energy price at first, but peaks while the latter is still growing and subsequently decreases before the energy price begins its downward trajectory driven by a rapidly growing share of renewables. Figure 5 shows the adjustments in the energy sector, which exhibits a strong increase in credit demand (Figure 5a). This is driven by the green sectors undertaking large investments (Figures 5b-5c) and by the fossil fuel sectors having to pay the carbon tax and sustain costly spare capacity (Figures 5d-5e). The consequent erosion of profitability affects financial stability, leading to an increase in defaults. Coal is especially affected, with default rates in this sector rising to 10-20% for 2°C and 1.5°C targets respectively (Figure 5f). Differently, oil and gas are only marginally impacted. This result confirms that rapid mitigation may generate imbalances harming the financial stability of high emitting sectors (e.g. Mercure et al., 2018), but these risks appear to be concentrated in specific areas (i.e. coal).

⁶During the recent energy crisis due to the Russian invasion of Ukraine, firms have generally been able to fully pass energy price shocks (Lafrogne-Joussier et al., 2023) on to final output prices and possibly even increase their mark-ups in the process, giving rise to so-called *sellers' inflation* (e.g. Weber et al., 2024; Weber and Wasner, 2023). Our assumption of full pass-through with largely constant markups can therefore be seen as qualitatively in line with available empirical observations and possibly even somewhat conservative.

Figure 4: Macroeconomic and distributional effects along 1.5°C pathways. **a**, blue and red lines represent averages across 300 simulations of the 1.5°C scenario, the red line is the wage share (right), blue line is the unemployment rate (left); **b**, blue and red lines represent averages across 300 simulations of the 1.5°C scenario, red line is the energy price (right), blue line is the inflation rate (left); **c**, scatterplot of unemployment and logarithm of the energy price, results pooled across 300 simulations of each scenario, period from 2015 to 2050, red line is a non-linear interpolation; **d**, scatterplot of wage share and logarithm of the energy price, results pooled across 300 simulations of each scenario, period from 2015 to 2050, red line is a non-linear interpolation.

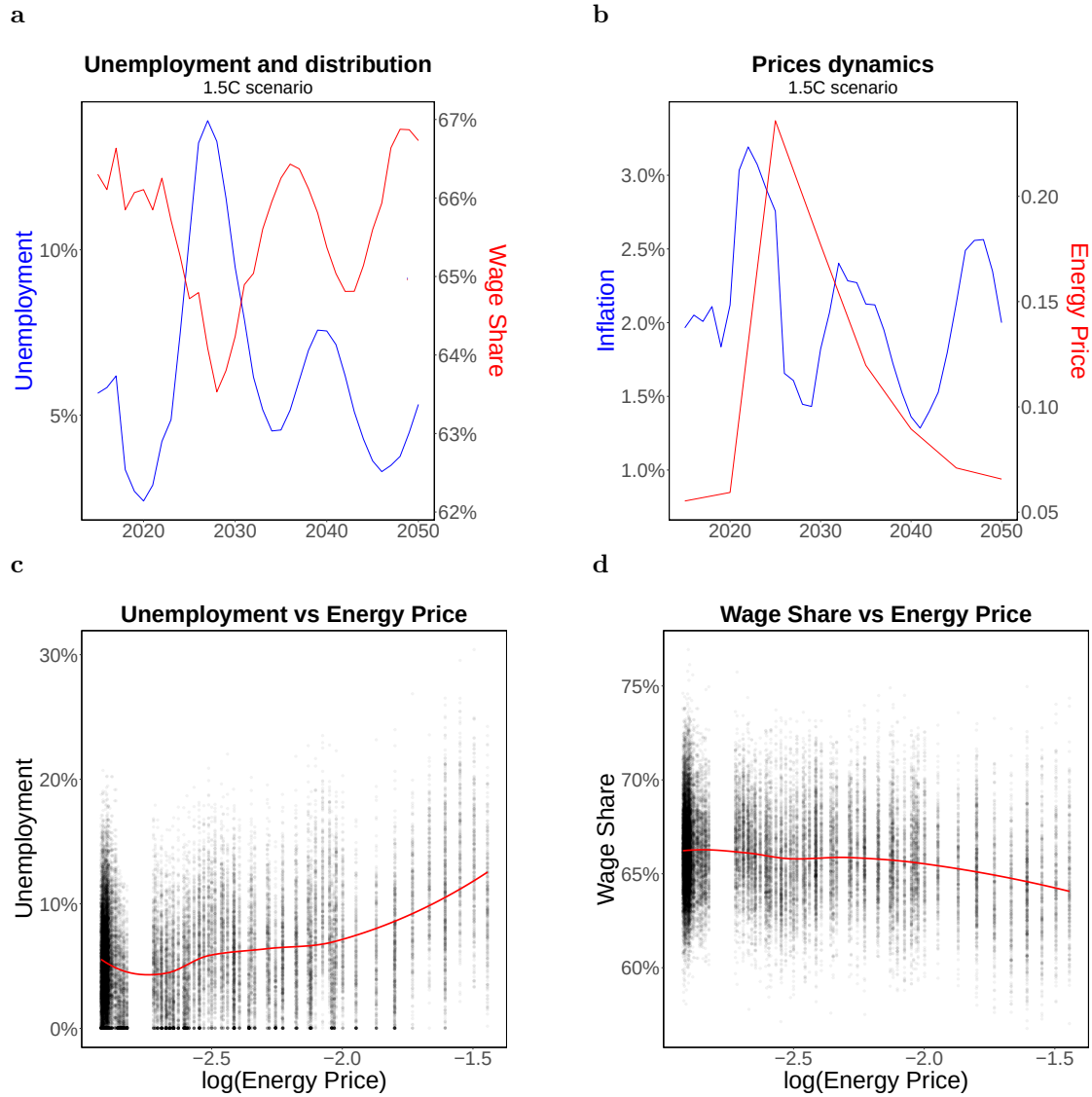
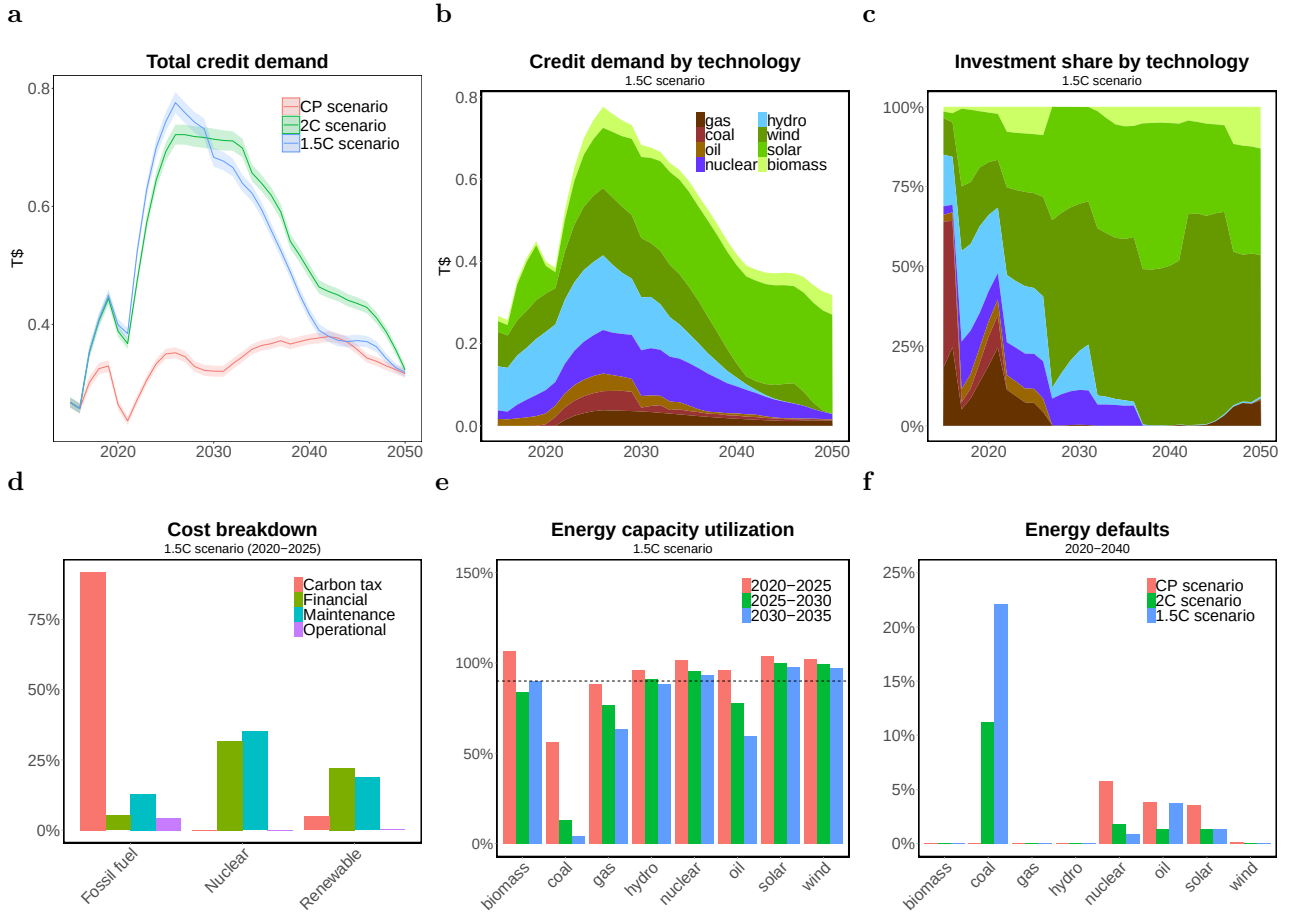


Figure 5: Energy sector-finance link, asset stranding and energy sector imbalances in 1.5°C pathways. **a-f**, averages across 300 simulations; **a**, total credit demand of the energy sector across scenarios, expressed in 2022 US T\$⁷. Shaded areas represent 95% confidence intervals; **b**, energy sector credit demand disaggregated by sub-sectors, 1.5°C scenario, expressed in 2022 US T\$⁸; **c**, investment disaggregated by energy sub-sector, 1.5°C scenario, expressed as a share of total investment in the energy sector; **d**, energy sectors costs broken down by cost type and disaggregated by technology-groups. Costs are expressed in proportion to revenues and refer to the 1.5°C scenario for the time window 2020-2025; **e**, capacity utilization disaggregated by energy sub-sector, calculated as the ratio between actual production and the maximum potential production, the horizontal discontinuous line marks target capacity utilization, which is set to 90%⁹; **f**, defaults disaggregated by energy sub-sector expressed as the average ratio of defaulted debt to total debt across simulations, grouped by scenarios, period 2020-2040.



⁸The model output is rescaled in order to obtain the credit demand figure in Trillion 2022 US\$. We calculate the energy sector-wide nominal credit-investment ratio produced by the model for 2022 in the CP scenario. We then multiply that ratio by the empirically observed nominal "power sector investment", as reported by the IEA *World Energy Investment 2023* (IEA, 2023), to infer the equivalent nominal credit demand expressed in Trillion 2022 US\$. Finally, we use this empirically inferred nominal credit demand for 2022 and its counterpart from the model to calculate a rescaling factor which is applied to the simulated time-series across all scenarios.

⁹Note that occasionally capacity utilization can slightly exceed 1. This is because the energy mix is an input taken from WITCH scenarios and, during the transition, some energy sub-sectors in DSK may not yet have obtained the entire capacity needed to satisfy the demand implied by the exogenous energy mix. Since such inconsistencies are small, we allow the respective sectors to exceed full capacity utilization and accommodate the demand implied by the energy mix taken from WITCH.

The role of monetary and fiscal policies

The simulations shown above point to disruptive business cycle fluctuations arising from the carbon pricing needed to stabilize global warming. So far, however, we did not consider potential monetary and fiscal policy responses. The central bank (CB hereafter) follows a single-mandate Taylor rule aimed purely at inflation stabilization (Section 1.1.6 in SI) and the government retains the entire carbon tax revenue.

To conduct a range of monetary and fiscal policy experiments, we relax these assumptions, allowing the CB to respond to unemployment and the government to redistribute carbon tax revenues. As was shown above, the dynamics generated by DSK in the 1.5°C and 2°C scenarios are qualitatively similar. We therefore conducted our policy analysis for the most stringent climate scenario (1.5°C). The alternative monetary policy rule modifies the single-mandate Taylor rule by adding an employment stabilization component that is activated when the unemployment rate exceeds a threshold, leading the central bank to lower its interest rate.¹⁰ The central bank’s reaction to unemployment is governed by an exogenous parameter, measuring the strength of the central bank’s reactivity to high unemployment: the larger the CB’s reactivity to unemployment, the lower the interest rate in case of high unemployment. The fiscal policy experiment involves the redistribution of the carbon tax revenue to households. We assume that a share of current carbon tax revenue is distributed to households as a lump sum transfer. Moreover, we assume that this transfer is treated as being equivalent to labour income, and hence that the same propensity to consume applies to it.

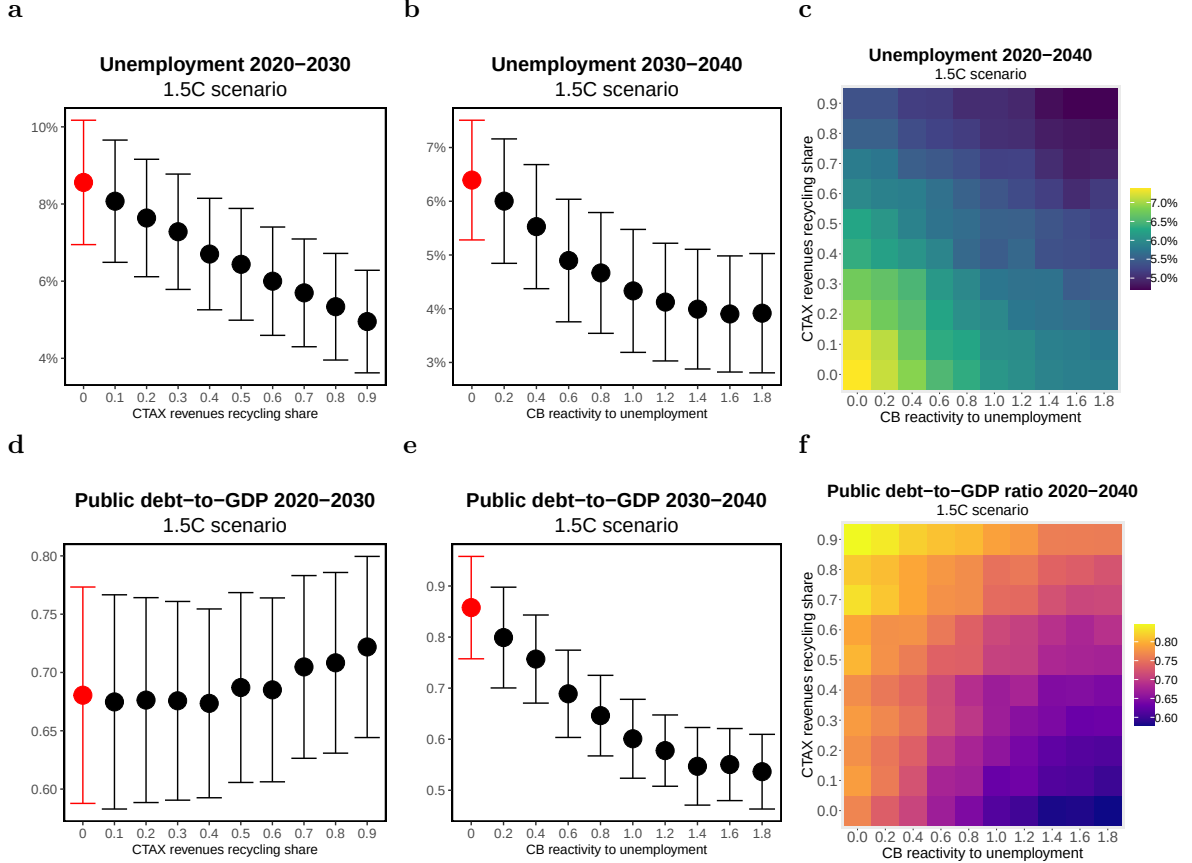
Results from our policy experiments are summarised in Figure 6. First of all, they suggest an important role for monetary-fiscal policy coordination to moderate the effects of the carbon tax. We focus on the most period, i.e. 2020-2040, which we split into two decades, and focus on unemployment and public debt-to-GDP ratios. In the first sub-period, fiscal policy is highly effective in reducing unemployment (Figure 6a). This is because, during this period, the carbon tax is high, resulting in large revenues to be redistributed. Monetary policy effects are instead negligible (Figure 6 in SI). This is because, in 2020-2030, the policy rate does not change much across different CB reactivity levels to unemployment (Figure 5 in SI). At the beginning of the transition phase, inflation rises faster than unemployment and hence dominates the Taylor rule. In 2030-2040, carbon tax revenues decline as emissions plummet, meaning that fiscal policy becomes less effective (Figure 7 in SI). However, we observe a stronger role for monetary policy during this period (Figure 6b). In 2030-2040, inflation recedes and so the employment stabilization effect dominates the Taylor rule, resulting in decreasing interest rates.¹¹

We also find that inflation is not responsive to monetary policy during the transition, meaning that lowering the policy rate to fight unemployment does not produce additional inflationary pressure (Figure 6 in SI). This is because inflation during the transition is driven by the energy price, which is exogenous to the policy rate. In the case of cost-push shocks, the main channel through which monetary policy could stabilize inflation is through expectation anchoring. However strong such a

¹⁰Effectively, we assume a *recession avoidance preference* for the CB (cf. Cukierman and Muscatelli, 2008) with some degree of “recession tolerance”, i.e. the policy rate response to unemployment is not asymmetrical around zero, but instead around a positive threshold level (cf. Bunzel and Enders, 2010). We set the threshold level at 10%, as this high unemployment rate can be considered an alarming indicator of a severe recession in most countries.

¹¹Central banks typically avoid abrupt changes in the policy rate; instead, they gradually adjust the policy rate towards a specific target. This behaviour is captured by the implemented Taylor rule (Equations 57 and 76 in SI). As a result, the policy rate responds with a certain lag after unemployment reaches its safeguard level and remains relatively low even after unemployment drops below this level (Figure 6 in SI). These two effects together determine the efficacy of monetary policy in the second phase of the transition.

Figure 6: Monetary and fiscal policy to stabilise the transition in 1.5°C pathways. **a-b** and **d-e**, dots refer to averages across 50 simulations, with each dot representing a policy experiment, red dots refer to the baseline configuration, bars are 95% confidence intervals; **a**, average unemployment rate, 2020-2030, 1.5°C scenario, across fiscal policy experiments, i.e. different shares of redistributed carbon tax revenues; **b**, average unemployment rate, 2030-2040, 1.5°C scenario, across monetary policy experiments, i.e. different degrees of CB reactivity to unemployment; **d**, average public debt-to-GDP ratio, 2020-2030, 1.5°C scenario, across monetary policy experiments, normalized at 2015 value; **e**, average public debt-to-GDP ratio, 2030-2040, 1.5°C scenario, across monetary policy experiments, normalized at 2015 value; **c**, average unemployment rate, 2020-2040, 1.5°C scenario, across monetary and fiscal policy experiments; **f**, average public debt-to-GDP ratio, 2020-2040, 1.5°C scenario, across monetary and fiscal policy experiments, normalized at 2015 value.



channel might be in the real world, it is absent from our model, meaning that we may underestimate the inflationary costs of an expansionary monetary policy along the transition.

The complementarity between fiscal and monetary policy hence stems from the fact that they are effective at limiting unemployment during different phases of the transition. Figure 6c illustrates their complementarity by pooling simulation data across phases. It shows that the average unemployment rate for the full 2020-2040 period is lowest when fiscal policy redistributes a high share of carbon tax revenue and monetary policy is expansionary. In addition, monetary-fiscal policy coordination also has relevant effects on the public budget (Figures 6d, 6e, 6f). In particular, a lower policy rate will tend to lower the cost of servicing public debt in the latter phase of the simulation, hence creating fiscal space. Additionally, we observe that carbon tax revenue redistribution has a largely neutral effect on public debt. When carbon revenue is not redistributed, this represents an additional source of general revenue for the government. At the same time, however, declines in GDP and employment imply that other tax revenues will tend to decline, while outlays for unemployment benefits increase.

Discussion

Mitigation pathways, such as those reviewed in IPCC reports (IPCC, 2022), offer a detailed assessment of decarbonisation dynamics that all key sectors should undergo to meet certain climate targets. However, in their current status, they fail to provide an informative picture of the imbalances that such a process can create at the macro-financial level. Further, they are silent on the behaviour of macroeconomic aggregates at the time scale (e.g. quarterly or annual frequency) that is relevant for designing stabilisation policies accompanying climate ones. This study combined the strengths of two complementary modelling approaches, IAM and MABM, to shed light on the macroeconomic and financial implications of mitigation scenarios. Process-based IAMs generate transition pathways with high technological detail, while the strength of MABMs lies in the joint depiction of short and long-run out-of-equilibrium economic dynamics, distributional feedback effects, and real-financial interactions. This, combined with MABMs' capacity to handle a wide range of relevant economic variables, renders the IAM-MABM link a valuable instrument for refining the estimation of transition costs across various dimensions and transmission channels.

By simulating detailed transition scenarios generated by the WITCH IAM in the DSK MABM, we showed that ambitious mitigation trajectories guided by carbon pricing - as the vast majority of pathways in the literature - induce perils to macro-financial stability. Indeed, we showed that scenarios compatible with 2° and 1.5°C tend to generate high unemployment and high inflation, resembling dynamics typical of so-called “stag-flationary” episodes. The source of the instability lies in the rapid transformation of the energy sector and its connection to the financial system. Our results point to the emergence of costly physical stranded assets in the fossil fuel-intensive sectors (see also [Mercure et al., 2018](#); [Semieniuk et al., 2022](#)), which contribute to an erosion of profitability of these sub-sectors during the transition. These decreases in profitability, in turn, result in an increased need for external finance as well as a higher rate of defaults. However, such risks concentrate in the coal sector, while gas and oil face much lower exposure.

Further, we showed that that an orderly (low unemployment) and just (low labour share losses) are not independent: they need to align. Indeed, the price of energy can be viewed as a distributional variable and shifts in functional income distribution resulting from climate policy can have undesired macroeconomic consequences. In particular, our results suggest that unless corrective policy action is taken, transition pathways guided by carbon prices are associated with temporary periods of high inflation and high unemployment. This volatility has detrimental consequences for the feasibility of decarbonization. These results point to the need (i) to account for ampler policy packages within mitigation pathways (e.g. [Wieners et al., 2024](#)), (ii) to report climate policy strength beyond carbon pricing.

Conducting a battery of fiscal and monetary policy experiments, we showed that redistribution of carbon tax revenue can play an important role in limiting the negative macroeconomic effects of carbon pricing during the early phase of the transition. Expansionary monetary policy, on the other hand, was found to be more effective during the later stages of the transition, suggesting a positive role for monetary-fiscal policy coordination.

Overall, our study emphasizes the importance of incorporating a macro-financial dimension into the analysis of mitigation pathways. This addition is essential for a more comprehensive assessment of the viability of decarbonization trajectories and the effectiveness of underlying climate policies. We demonstrate that integrating macroeconomic models with integrated assessment models is a promising

approach, although several limitations must be addressed in future research. Specifically, adopting a more disaggregated perspective at the country or macro-regional level is essential to offer clearer insights into practical policymaking. Our soft-link approach also entails limitations for certain avenues of analysis, notably the design of the carbon tax. While our main exercise is intended to assess the macroeconomic consequences of carbon tax trajectories generated by an IAM once implemented in a full-fledged macroeconomic ABM, a natural extension would be to explore a hard coupling of the two models. This would allow the carbon tax to become endogenous to the economic dynamics generated by the ABM itself. We view our contribution as a necessary foundation for this line of research, paving the way towards full IAM–ABM integration.

Online Methods

This study integrates an agent-based macroeconomic model and a process-based integrated assessment model to assess the materiality of transition risks along ambitious (deep) mitigation pathways. Detailed descriptions of the two models can be found in [Reissl et al. \(2024\)](#) (DSK) and [Emmerling et al. \(2016\)](#) (WITCH). Additionally, a thorough discussion of key model features, including necessary extensions to the DSK framework for coupling with WITCH, is provided in Section 1 of the SI. In this section, we outline the main model features relevant to our analysis.

The economic core of the DSK model is formed by two vertically integrated agent-based firm sectors, namely consumption good firms and capital good firms (C-Firms and K-Firms hereafter). K-Firms produce machines characterised by heterogeneous labour productivities, energy efficiencies and emission intensities. To produce them, K-Firms use production techniques which are also heterogeneous in terms of labour productivity, energy efficiency and emission intensity. New capital goods and production techniques are the product of K-Firms’ R&D, which determines long-term growth.

C-Firms use machines, labour, and energy to produce a homogeneous consumption good. C-Firms buy machines to match expected demand. Firms’ activities are financed through retained earnings and, in the case of C-Firms, loans from a banking sector. Households consume and receive income in the form of wages for supplied labour, interest on deposits, dividends from firms, banks and the energy sector, as well as unemployment benefits and occasional government transfers (like redistributed carbon tax revenues). The government collects taxes and spends on unemployment benefits, transfers, and the bailout of failing banks, while the central bank sets the policy rate. The DSK model also includes an energy sector which supplies the firm sector with the energy needed for production, invests in physical capital and finances its activities using internal funds and bank credit.

The consumption and capital goods sectors, as well as the banking sector, consist of multiple and heterogeneous agents. We leverage the MABM framework to agentify the WITCH energy sector into eight macro-agents, each representing a distinct energy technology. Households are modelled as an aggregate entity. Table 2 in SI shows the transaction flow matrix of the model, summarising the transactions between sectors and how these are financed.

The balance sheet and transaction flow matrices (Section 1, Tables 1-2 in SI) can be used to derive the accounting identities that must be satisfied for the model to be formally stock-flow consistent. To ensure stock-flow consistency during simulations of the model, all transaction flows and balance sheet items are explicitly tracked. At the end of each simulation period, the model performs a series of checks at the agent, sectoral and aggregate levels to ensure that no accounting identities have been violated during the period.

The WITCH model is an integrated modelling framework that captures the interactions among climate change, energy systems, and economic growth. It combines a macroeconomic model with a detailed energy system. The macroeconomic (top-down) aspect uses an intertemporal optimization strategy that incorporates macroeconomic relationships and dynamics over time. Simultaneously, the energy system (bottom-up) component details the technology options available in the energy sector. This dual approach facilitates the cost-effective optimization of strategies to minimize global costs associated with achieving specific climate and energy targets, taking into account investment, operational costs, the repercussions of climate change, and policy instruments such as carbon pricing.

The model divides the world into distinct global regions and generates optimal mitigation pathways up to 2100. These pathways are obtained through a welfare maximization process that accounts for regional interactions and the strategic dynamics spawned by global externalities, employing an iterative method to achieve a non-cooperative Nash equilibrium.

WITCH is distinguished by its dynamic representation of R&D diffusion and innovation in energy efficiency and low-carbon technologies. It encapsulates the broad spectrum of externalities in climate and innovation policy, including the global sharing of knowledge and technology spillovers, which influence each country’s adoption of low-carbon technologies and energy productivity. This is based on regional energy research and development, capital stocks, and the global cumulative installed technology capacity.

From an economic point of view, the model simulates a single-sector economy, where output may be influenced by climate impacts (climate change impacts are not activated in this study), and costs related to fossil fuel use and greenhouse gas mitigation are accounted for. It employs a social planner perspective to optimize regional utility, including risk aversion to future consumption levels. A CES function represents the production of goods using capital, labour, and energy services.

The energy sector within the WITCH model covers a broad spectrum of primary energy sources, conversion technologies, and consumption sectors. It includes diverse energy carriers, from fossil fuels to renewables, and technologies, from power generation to transportation, representing technological advancements and energy efficiency gains over time.

The scenarios generated for this study follow standard policy designs. The Current Policy scenario implements current national climate policies and extrapolates the same effort level across the century using regional carbon prices. Regulations and emission constraints are maintained throughout the century. The climate policies ‘2C’ and ‘1.5°C’ aim for global net-zero emissions, following the design presented in [Rogelj et al. \(2019\)](#). Starting from 2020, a global carbon tax is implemented to reduce CO₂ emissions. Once CO₂ emissions reach net zero, global emissions are maintained at this level until the end of the time horizon. Until the net-zero year, the carbon price is set to limit cumulative emissions to 1000 GtCO₂ for the ‘2C’ scenario and 500 GtCO₂ for the ‘1.5°C’ scenario. Thereafter, the carbon price is adjusted to equal the emission market price to stabilize emissions at zero globally. More details about these two scenarios can be found in [Drouet et al. \(2021\)](#) and [Riahi et al. \(2021\)](#).

To couple the two models, we establish a one-way link from WITCH to DSK. Specifically, technology and cost-related variables for the energy sector, along with energy and carbon prices from transition scenarios generated by WITCH, are fed into DSK (see [Figure 1](#)). We chose these variables to partially replace the DSK energy sector with that of WITCH. The resulting energy-level variables — such as production, investment, and credit demand — emerge from the interaction between the two models. This interaction combines the microeconomic variables from WITCH (e.g., operation and maintenance costs, energy mix) with the macroeconomic variables from DSK (e.g., aggregated

WITCH-DSK coupling

Coupling output	WITCH	DSK	Coupling output
Coupled energy price	Energy price	Inflation	
Energy production	Energy mix	Aggregate energy demand	
Energy expenditures		Aggregate energy demand	Coupled energy price
Coupled carbon tax	Carbon tax	Inflation	
Capacity expansion		Target capacity utilisation	Energy production
Capacity	Capital depreciation		Capacity expansion
Nominal investment	Unit costs of investment Capacity factor		Capacity expansion
Fixed costs	Maintenance costs		Capacity
Operating costs	Production costs		Energy production
Emissions	Emission intensities		Energy production
Carbon tax payments			Emissions Coupled carbon tax
Credit demand		Loan refinancing Deposits	Operating costs Fixed costs Nominal investment Carbon tax payments

Table 1: The first column lists the variables that result from combining WITCH inputs with endogenously produced variables from DSK. The second and third columns indicate which variables from WITCH and DSK are used to produce a particular coupling output variable. The last column indicates that some coupling outputs are recombined with WITCH and/or DSK variables to produce additional coupling outputs.

energy demand, financial conditions). Table 1 illustrates how the variables from WITCH and DSK are combined, along with the resulting outputs. For more detailed information, please refer to the SI.

WITCH produces scenarios up to 2100. For the current exercise, we only examine their effect on DSK dynamics up to 2050, which is the phase during which the transition takes place in decarbonization scenarios. Since DSK is a single-region model, global-level variables from WITCH are used as inputs. Section 1.4 in the SI discusses the calibration and the empirical validation of the modelling framework used in this work.

Macroeconomic policies and climate policies run together in the coupled model. Climate policy is implemented into WITCH, while fiscal and monetary policies are set in DSK. Section 1 of the SI provides additional insights into the policy rules adopted. Section 2 in the SI discusses the transmission of the climate policy shocks at the macroeconomic level (see Section 2.1) and provides additional results on the stabilizing effects of monetary and fiscal interventions (see Sections 2.2 and 2.3, respectively).

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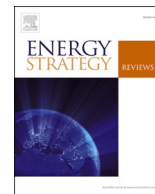
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International knowledge spillovers in energy technologies

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ABSTRACT

This study examines the impact of barriers to knowledge diffusion in energy technologies in 29 countries from 1990 to 2015, distinguishing between efficient fossil-based generation and mature renewable options, namely wind and solar. We show that knowledge flows are higher in countries with similar technological profiles, particularly for mature renewables. The study finds that international knowledge spillovers have increased in intensity for wind and solar, while the opposite is true for fossil-based technologies. That means that foreign knowledge has increasingly informed domestic investors and points to the key role that knowledge flows from abroad had in promoting innovation in low-carbon technology options. Integrated assessment models should account for the role international knowledge spillovers play in the generation of new knowledge and in contributing to rapid decrease in costs.

1. Introduction

Knowledge flows play an important role in (low-carbon) innovation. Existing literature shows that innovators build on the knowledge in their own country but also source knowledge from foreign inventor when they push the frontiers of their own knowledge [1]. Innovations in low-carbon technologies benefit from intertemporal knowledge spillovers [2] as well as from international knowledge spillovers [3]. In this paper, we focus on estimating the extent to which inventors in one country rely on foreign knowledge. This is an important research question because to date advanced climate mitigation technologies have been developed only by a handful of countries [4]. These small groups of countries play a big role in inventing and diffusing new and improved low-carbon energy technologies. Yet, to achieve stringent decarbonisation targets, low-carbon energy technologies have to be adapted to local conditions, and further improved [5]. In this context, a better understanding of how knowledge flows across countries is needed.

This paper presents an up-to-date analysis of international knowledge flows and spillovers in two key sets of low-carbon energy technologies: efficient fossil-based and mature renewable energy technologies. These two families of technologies play very different roles in decarbonisation pathways. Efficient fossil-based technologies are those which reduce energy use and carbon emissions by improving energy efficiency of fossil-fuel based power generation technologies [6].

These include, for instance, highly efficient gas-based generation technologies. Mature renewable energy technologies are those which can produce energy with no associated greenhouse gas emissions [7]. In this analysis, we restrict our attention to wind and solar technologies because they are the ones where significant reduction in costs have been achieved thanks to innovation and learning-by-doing dynamics over the last two decades. These technologies are now cost-competitive with fossil-based energy generation technologies [8]. Understanding the knowledge flows dynamics which have accompanied this large decrease in cost, and how they differ from knowledge flows patterns in fossil-based technologies, is an interesting case study which can inform future innovation policies as well as climate mitigation efforts.

Our econometric approach builds on Peri [9] and Verdolini and Galeotti [3]. We postulate that spillovers depend on the ability to overcome key geographical, linguistic, economic, technological and policy-related knowledge diffusion barriers. This is in line with the extant literature, that shows that knowledge flows are reduced due to geographical [10], linguistic barriers [11] and trade barriers [12], while they are higher the more similar the technological expertise of two given countries [13] and the lower the distance in the policy space [14].

We use data for 29 countries, including fast-developing economies, over the years 1990–2015 to estimate the role of different knowledge diffusion barriers in mature renewable technologies as opposed to efficient fossil-based generation. We focus both on the overall sample

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period as well as on two sub-periods (1990–2002 and 2003–2015) to test whether the strength of different diffusion barriers has changed over time. This split is motivated by the fact that in 2003 the EU adopted the European Union (EU) Emissions Trading System (ETS) Directive [15]. We also explore the extent to which changes in spillovers patterns depend on the relative stringency of environmental policies of the source and the receiving country. Our paper differs from existing analysis because it focuses on a large set of countries and compares knowledge flows in two different technological domains. Grafström analyses international knowledge spillover in wind power from 1978 to 2008 using patent data [16]. Peter shows evidence of policy-induced knowledge spillover in solar Photovoltaics (PV) in 15 Organisation for Economic Cooperation and Development (OECD) countries from 1978 to 2005 [17].

Overall, we show that spillovers change over time, and do so differently for mature renewables as opposed to efficient fossil-based technologies. Geographical barriers reduce knowledge flows across both technological domains, but their role changes over time: geographical distance hindered knowledge flows comparatively more in mature renewables as opposed to efficient fossil-based technologies in the period 1990 to 2002, but not afterwards. Mature renewable energy knowledge flows easier across linguistic border than does fossil-based technology knowledge flows. Trade barriers do not hinder knowledge flows in either types of technologies. Technological distance hinders knowledge flows similarly in the period up to 2002 for mature renewables as opposed to fossil-based technologies, but in the following period matters more for wind and solar, suggesting that as technologies mature, it is harder for knowledge to flow to countries which do not have a similar technological profile.

We use our empirical results to build knowledge spillover matrixes that can be fruitfully used by modellers to update the calibration of knowledge production functions in integrated assessment model (IAMs) and more realistically model international knowledge spillovers. From a modelling point of view, overlooking the knowledge spillover effects that occur across countries may lead to an underestimation of the speed at which technology costs may decrease, or, conversely, and overestimation of the costs of compliance with stringent climate policy as we would underestimate the possibility that a given country builds on foreign knowledge to further innovate domestically.

2. Method and data

To examine the role of geographical, linguistic, economic and technological barriers in hindering knowledge flow across countries, we build on Peri [9] and Verdolini and Galeotti [3]. Specifically, as customary in the innovation literature, we use patents as an indicator of an innovation having taken place; citations between patents of different countries are considered a proxy of international knowledge flows [3,9,18–20]. The advantage of using patent and patent citation indicators lies in the richness of information they provide. Patents can be relatively easily classified as belonging to a given technology field and country. Patent citations represent a “trail” of knowledge flows: it is mandatory for inventors to cite “prior art.” For these reasons, these data have been widely used, although they still suffer from several shortcomings. These include the fact that patent counts do not reflect commercial value of the innovation and may be the results of strategic patenting behaviors, and the fact that patent citations may be only a partial proxy of knowledge flows [21].

Our baseline econometric model is as follows:

$$c_{ij} = \exp \left[a_i + a_j + \sum_{n=1}^7 b_n x_{n(i,j)} + \mu_{ij} \right] \quad (1)$$

The number of total citations c received from patents in country i from patents in country j within 5 years of the application date of the cited patent is a function of citing country and cited country fixed effects

(a_i and a_j) and of a number n of diffusion barriers x . We compute c_{ij} for both mature renewables and for efficient fossil-based technologies for the full sample period (1900–2015) and for two sub-periods (1990–2002 and 2003–2015).

The citing and cited countries fixed effects a_i and a_j control for the different propensity to patent and to cite across countries. Conversely, the $x_{n(i,j)}$ variables represent time-invariant geographical, linguistic, economic and technological barriers to knowledge flows, and are defined as follows:

$x_{1(i,j)}$ is a dummy variable equal to 1 if the citing and cited countries are different. We expect the coefficient b_1 associated with $x_{1(i,j)}$ to be negative, indicating that any country would cite foreign patents less frequently than domestic patents [22].

$x_{2(i,j)}$ is the geographical distance between citing and cited countries based on the longitude and latitude. The distance data is measured by the shortest geographical distance (most populated cities, km) from GeoDist database [23].¹ We expect the coefficient b_2 associated with $x_{2(i,j)}$ to be negative, implying that an increase in geographical distance further lowers the probability of citation [24].

$x_{3(i,j)}$ is a dummy variable equal to 1 if the citing and cited countries have different official languages, and equal to 0 if they have at least one official language in common. The official language refers to languages spoken by at least 20% of the population of the country. As a country can have several official languages, we compare up to three official languages based on the database [25]. This index captures the presence of linguistic barriers. We expect the coefficient b_3 associated with $x_{3(i,j)}$ to be negative, indicating that knowledge flows are higher between countries which share a common language [11].

$x_{4(i,j)}$ measures trade barriers. The variable is calculated as the share of years in which the citing and cited country are not part of the same Free Trade Agreement (FTA). When this index is equal to one, the two countries are never part of the same FTA for the whole sample period (or analysed subperiods). When it is equal to zero, the two countries are always part of the same FTA. Belonging to the same FTA is based on Mario Larch's Regional Trade Agreements Database [26]. We expect the coefficient b_4 associated with $x_{4(i,j)}$ to be negative as trade borders represent barriers for knowledge flows [27].

$x_{5(i,j)}$ is an index that varies between 0 and 1 and measures technological distance in innovation between the citing and the cited country over the whole sample period (or sub-periods). Or the corresponding sub-period when we estimate equations for different time periods. The index is adapted from Jaffe [28] and calculated as follows:

$$x_{5(i,j)} = 1 - \frac{(h'_i h_j)}{\left[\sum_s (h'_{i,s})^2 (h_{j,s})^2 \right]^{1/2}} \quad (2)$$

Where h is a share of patents in each technology field s (Appendix Table A1) for the entire period of study. When the index is equal to 1, the countries that have completely different innovation profiles, i.e., their innovation efforts are focused on completely different technologies. Conversely, when the index is equal to 0, the countries are completely similar in their innovation profile. The coefficient b_5 associated with $x_{5(i,j)}$ is expected to be negative. This implies that the more similar the two countries are in technology space, the more likely they are to cite each other [29].

$x_{6(i,j)}$ is an index measures distance in the level of technological development of the citing country i with respect to the cited country j in each technology fields (Appendix Table A1). The index is based on [30] and is calculated as the ratio of the average number of citations received

¹ It is note that we added two missing countries from the database manually (e.g. Liechtenstein (latitude = 47.166 and longitude = 9.5554) and Monaco (latitude = 43.733334 and longitude = 7.416667)).

Table 1

Summary statistics of patents by innovating countries for mature renewable energy (upper panels) and fossil-based (lower panels) technologies, 1990–2002 (left) and 2003–2015 (right).

Citing country	Mature renewable technologies 1990–2002				Mature renewable technologies 2003–2015			
	No. of patents	% over sample	No. of citations	% over sample	No. of patents	% over sample	No. of citations	% over sample
DE	410	23.87	1039	19.98	4169	21.23	20,331	18.02
CH	379	22.06	1032	19.85	2386	12.15	12,387	10.98
US	291	16.96	1146	22.04	3799	19.34	29,837	26.44
JP	207	12.04	692	13.31	1174	5.98	5589	4.95
NL	75	4.35	191	3.67	464	2.36	2269	2.01
DK	60	3.48	113	2.17	1569	7.99	9321	8.26
GB	59	3.41	212	4.08	849	4.32	5018	4.45
FR	45	2.64	117	2.25	941	4.79	3909	3.46
IT	40	2.32	126	2.42	570	2.90	2618	2.32
AU	36	2.10	111	2.14	158	0.80	783	0.69
BE	34	1.95	88	1.69	213	1.08	1276	1.13
SE	22	1.28	118	2.27	165	0.84	691	0.61
AT	21	1.20	75	1.44	189	0.96	1275	1.13
ES	10	0.59	20	0.38	727	3.70	3825	3.39
NO	7	0.38	41	0.79	99	0.50	674	0.60
CA	6	0.36	33	0.63	175	0.89	1320	1.17
IE	5	0.26	16	0.31	29	0.15	180	0.16
FI	3	0.17	6	0.12	92	0.47	390	0.35
KR	3	0.17	7	0.13	1124	5.72	6842	6.06
RU	2	0.09	3	0.06	41	0.21	199	0.18
HU	1	0.08	7	0.13	11	0.05	31	0.03
CN	1	0.06	–	–	463	2.36	2523	2.24
PL	1	0.06	1	0.02	29	0.15	105	0.09
PT	1	0.06	1	0.02	26	0.13	131	0.12
IN	1	0.04	3	0.06	144	0.73	1065	0.94
SI	1	0.03	1	0.02	7	0.04	24	0.02
BR	–	–	–	–	12	0.06	77	0.07
CZ	–	–	–	–	8	0.04	50	0.04
GR	–	–	–	–	11	0.06	88	0.08
Citing country	Fossil-based technologies 1990–2002				Fossil-based technologies 2003–2015			
	No. of patents	% over sample	No. of citations	% over sample	No. of patents	% over sample	No. of citations	% over sample
US	254	30.29	794	35.40	632	29.86	4809	46.85
CH	169	20.11	466	20.78	290	13.71	1220	11.89
DE	162	19.27	337	15.02	423	19.98	1103	10.75
FR	49	5.88	153	6.82	146	6.88	605	5.89
GB	41	4.92	129	5.75	93	4.37	604	5.88
JP	34	4.09	110	4.90	52	2.46	164	1.60
SE	21	2.45	39	1.74	61	2.89	195	1.90
FI	18	2.12	21	0.94	40	1.88	118	1.15
IT	18	2.10	30	1.34	79	3.73	230	2.24
NL	17	2.02	35	1.56	27	1.28	75	0.73
DK	10	1.19	16	0.71	24	1.15	69	0.67
CA	10	1.13	17	0.76	30	1.39	348	3.39
AU	9	1.07	24	1.07	16	0.73	62	0.60
NO	7	0.81	31	1.38	15	0.72	60	0.58
AT	7	0.77	3	0.13	32	1.51	47	0.46
BE	5	0.54	6	0.27	18	0.84	69	0.67
BR	2	0.22	14	0.62	2	0.09	4	0.04
ES	2	0.18	5	0.22	12	0.54	51	0.50
RU	2	0.18	–	–	2	0.09	7	0.07
GR	1	0.12	3	0.13	4	0.19	22	0.21
HU	1	0.12	3	0.13	4	0.19	11	0.11
IN	1	0.12	2	0.09	31	1.48	129	1.26
KR	1	0.12	1	0.04	46	2.18	134	1.31
CN	1	0.06	–	–	20	0.92	83	0.81
PL	1	0.06	2	0.09	10	0.45	19	0.19
SI	1	0.06	2	0.09	2	0.09	4	0.04
CZ	–	–	–	–	6	0.29	14	0.14
PT	–	–	–	–	2	0.07	8	0.08

Notes: self-citations (citations to the same assignee) are excluded. Country names and two-letter codes by Patent Cooperation Treaty (PCT) applicant's guide. A list of countries: AT (Austria), AU (Australia), BE (Belgium), BR (Brazil), CA (Canada), CH (Switzerland), CN (China), CZ (Czech Republic), DE (Germany), DK (Denmark), ES (Spain), FI (Finland), FR (France), GB (United Kingdom), GR (Greece), HU (Hungary), IE (Ireland), IN (India), IT (Italy), JP (Japan), KR (Republic of Korea), NL (Netherlands), NO (Norway), PL (Poland), PT (Portugal), RU (Russia), SE (Sweden), SI (Slovenia), US (United States).

by patents in citing country i to the average number of citations received by patents in the cited country j within the same technological field s , minus one:

$$x_{6(i,j)} = \sum_s \left(\frac{f_{i,s}}{f_{j,s}} \right) - 1 \quad (3)$$

Unlike other variables, $x_{6(i,j)}$ can take both positive or negative values. It is less than zero if the low-carbon technologies patents of the

citing country give rise to fewer knowledge spillovers (i.e., they are less cited) than those granted to the cited country. Conversely, it is greater than zero if the patents granted to the citing country give rise to more knowledge spillovers (i.e., they are more cited) than those granted to the cited country. An index of 0 indicates that the patents granted in the citing country are on average as cited and important as those by the cited country [9]. We expect the coefficient b_6 associated with $x_{6(ij)}$ to be negative, implying knowledge flows are from the frontier countries and towards the laggard countries [3].

In addition to the traditional variables measuring geographical, linguistic, trade and technological distance, we also estimate a model which accounts for distance in the space of environmental policies. A few recent analyses have put forward suggestive evidence that distance in the environmental policy space may affect the rate of knowledge flow between two countries. Conti et al. [31], for instance, show that knowledge flows increase as together among those countries of the EU as a consequence of the increase in the stringency in environmental policies. Dechezleprêtre et al. [32] show that the similarity of environmental policy stringency between two countries positively matters for knowledge spillovers. Similarly, Milani [33] argues that market-based environmental policies increase cross-country knowledge collaboration on the ground that innovators innovate to respond to regulation.

The index measuring distance in the policy space is built using data from the OECD Environmental Policy Stringency Index (EPS) database. The EPS provides country-specific measures of the stringency of several environmental policy instruments over the years 1990–2011 [34]. The index is calculated as follows:

$$x_{7(ij)} = 1 - \frac{(k_i k_j)}{[\sum_s (k'_{i,p})^2 (k'_{j,p})^2]^{1/2}} \quad (4)$$

Where k is the percentage share of the sum of environmental policy stringency across all years (1990–2011) and different types of policy instruments (p). These include R&D subsidies, taxes, trading schemes, feed-in-tariffs, and standards. The index $x_{7(ij)}$ ranges between 0—indicating countries with completely similar policy profiles—and 1—indicating completely different policy profiles. A negative coefficient b_7 associated with $x_{7(ij)}$ would imply that the more similar the policy portfolios in the two countries, the higher knowledge flows [33]. We expect the coefficient b_7 to be negative, implying the higher the policy distance hinders the knowledge flows [14].

Using the estimated parameters from equation (1), we then generate diffusion parameters $\hat{\Phi}_{ij}$ defined as:

$$\hat{\Phi}_{ij} = \exp \left[\sum_{n=1}^N \hat{b}_n x_{n(ij)} \right] \quad (5)$$

Where $\hat{\Phi}_{ij}$ is the estimated probability of knowledge flows from cited country j to citing country i . In practice, $\hat{\Phi}_{ij}$ represents the portion of knowledge flows that can be predicted to occur between two countries given their geographical, linguistic, trade and technological distance. In this approach, intertemporal knowledge flows from domestic knowledge $\hat{\Phi}_{ii}$ is equal to 1 by construction, as all distance variables between country i and itself would be zero. Conversely, $\hat{\Phi}_{ij} < 1$ because only a fraction of the knowledge produced in i will reach j after passing geographical, linguistic, economic and technological barriers. In this context, $\hat{\Phi}_{ij}$ represents the probability of citation from patents invented in country i and year t to patents invented in country j between the years $t-1$ and $t-5$ relative to the probability that any inventor from country i cites a patent originating from country i over the same time period.

The econometric exercise we carry out is structured as shown in Fig. 1. In first instance, we provide estimates of equation (1) for both mature renewable energy and efficient fossil-based technologies. This is meant to highlight any difference in average knowledge flows for these

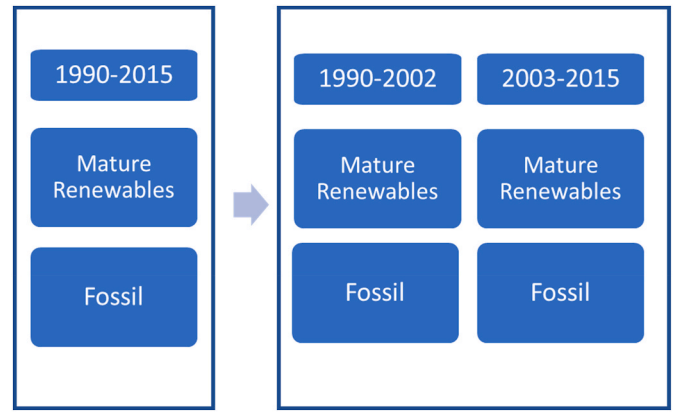


Fig. 1. Flow flowchart.

two very different sets of options over the entire sample period. Second, we split our sample into two periods (1990–2002 and 2003–2015) and repeat the estimation for both technology groups. This allows us to gauge any changes in spillovers intensity over time. Third, we repeat the analysis including an indicator measuring distance in the environmental policy space to test whether this plays a role in the diffusion of knowledge. Equation (1) is estimated using a negative binomial approach to account both for the count data nature of the dependent variable and for the over-dispersion in the data [35,36].

To identify mature renewable and fossil-based technologies, we follow a tagging system by the European Patent Office (EPO). We categorise the relevant patents by technologies defined by Y02 (climate change mitigation technologies) as of January 2018. Appendix A shows how we define technology fields and merge each table in the EPO's Worldwide Patent Statistical Database (PATSTAT) 2020 Autumn Edition.

We consider citing patents (i.e., mature renewables and efficient fossil-based energy technologies) applied for between 1990 and 2015, and cited patents applied for between 1985 and 2014 (in line with our 5 year-citation lag). The countries in our sample include 29 countries including key developing countries (e.g., China, India, Russia, Brazil). We consider all possible combinations of citing-cited countries, for a total of $29 \times 29 = 841$ observations. If a given country never cites another given country, we input zero citations.

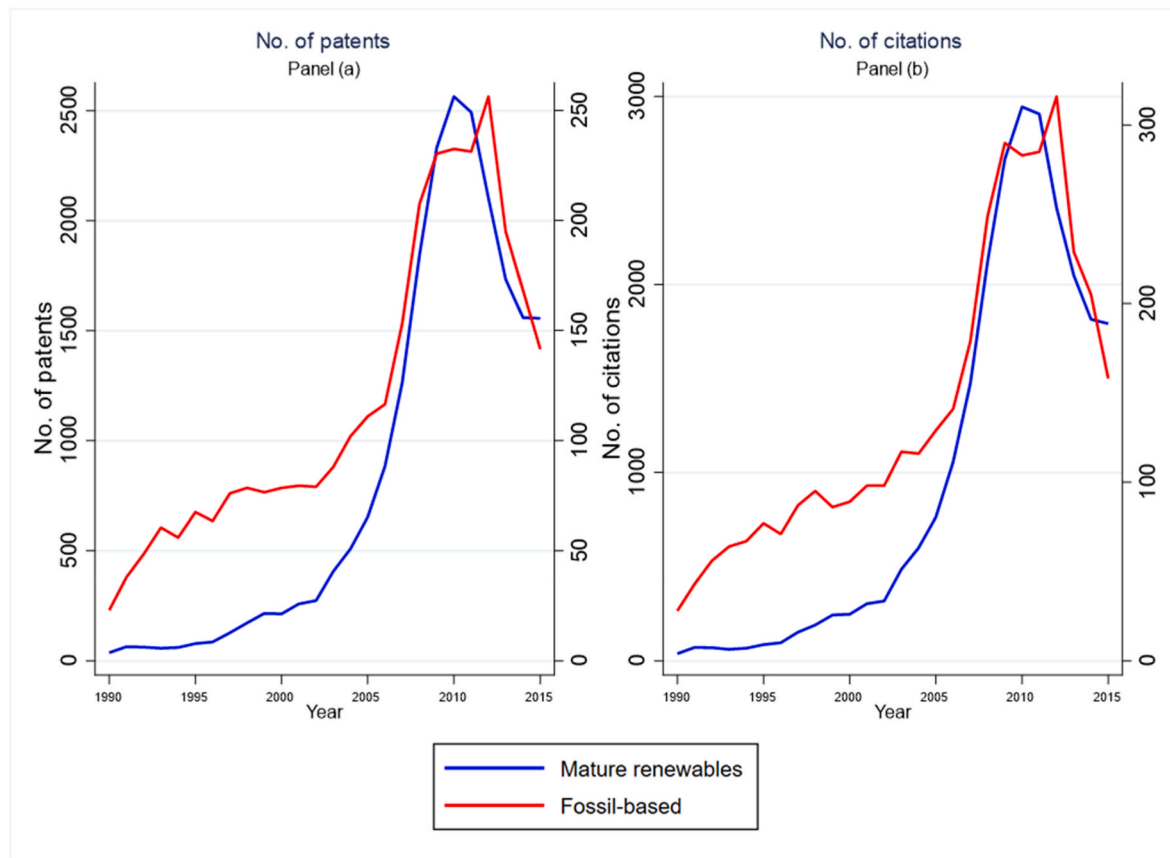
3. Results and discussion

3.1. Descriptive analysis

Fig. 2 shows the number of patents and the number of citations in our sample—Panel (a) and Panel (b), respectively—to examine temporal trends. The number of patents for both technological fields skyrocketed after 2002 and peaked around in 2010, after which they started to decline [37]. Innovation dynamics differ significantly for the two sets of technologies in our analysis: in 2010, the peak year, mature renewable patents were 67-fold higher than in 1990. Conversely, in 2010, fossil-based patents were 10-fold higher than in 1990. Afterwards, the number of patents decreases for both technologies; this is a natural consequence of the truncation of our data, as more recent patents take time to be recorded in the data.

Citation patterns exhibit a similar pattern. Citation dynamics also differ significantly for the two sets of technologies: in 2010, the peak year, mature renewable patent citations were 75-fold higher than in 1990. Conversely, fossil-based patents were 10-fold higher in 1990.

Table 1 shows the number of patents, share of patents over sub-sample, citations and share of patent citations by innovating countries for both sets of technologies and for the two sub-periods. Mature renewables and fossil-based patents represent 88% and 12% of the sample,



Notes: The number of patents in mature renewables and fossil-based technologies in Panel (a) is on the left and right side of the axis, respectively. The number of citations in mature renewables and fossil-based technologies in Panel (b) is on the left and right side of the axis, respectively.

Fig. 2. Number of patents (panel a) and citations (panel b) for mature renewables and fossil-based technologies

Notes: The number of patents in mature renewables and fossil-based technologies in Panel (a) is on the left and right side of the axis, respectively. The number of citations in mature renewables and fossil-based technologies in Panel (b) is on the left and right side of the axis, respectively.

respectively. For both types of technologies, Germany, Switzerland and the US are the top three inventors as well as the countries which receive the most citations. Together, these countries account for 63% (53%) of mature renewable energy patents and for 70% (64%) of fossil-based patents in the first (second) period. The corresponding percentages in terms of citations received are 62% (55%) for mature renewables and 71% (70%) for fossil-based technologies. Different countries follow in

the ranking of both patent numbers and citations received.

Table 2 shows the descriptive statistics of the dependent variable, citations from country j to country i , and of our control variables measuring geographical, linguistic, economic and technological barriers between countries and distance in the policy space. This is balanced panel data with a lot of 0's in the dependent and independent variables. The average number of citations in our sample is 203, with a standard deviation of 1,032, indicating large variations. Within country citations account for 3% of our sample; 89% (78%) of knowledge spillovers cross a linguistic border (trade border). The average distance in technological and policy space are 0.27 and 0.12, respectively; also in this case there is considerable variation in the sample.

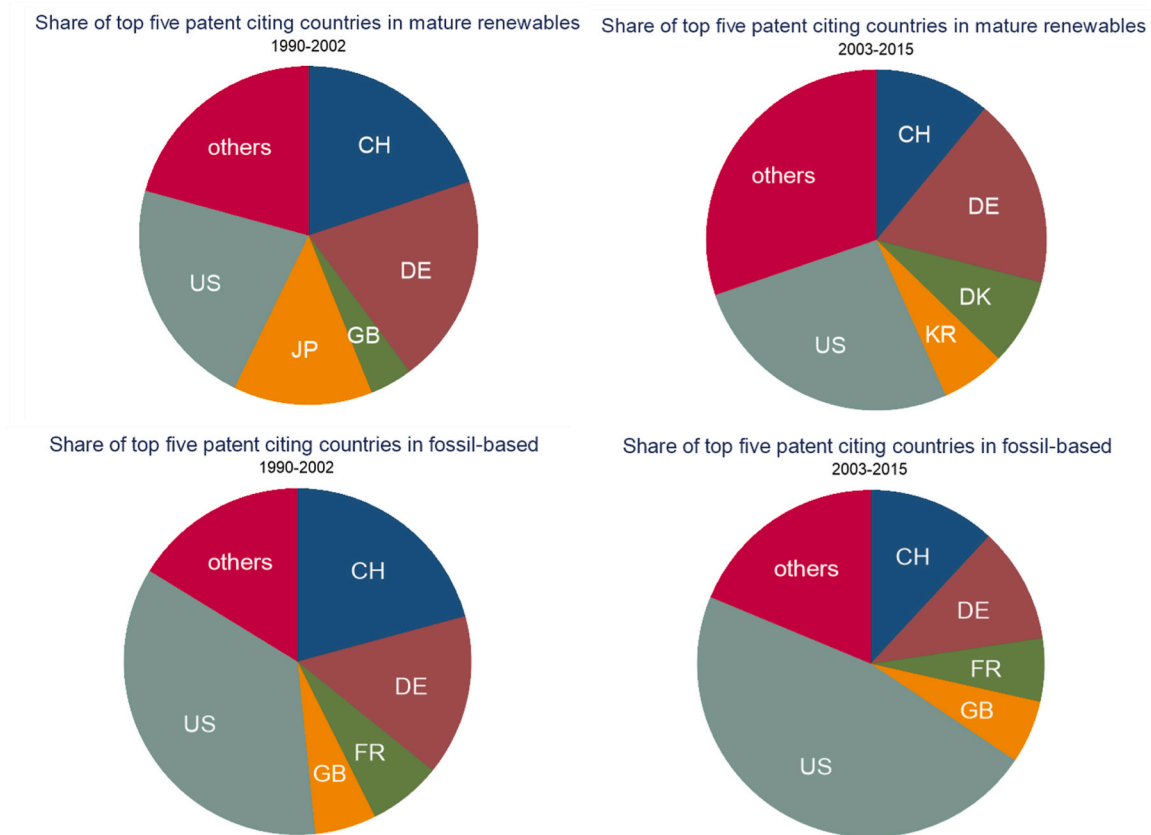
Fig. 3 shows the share of citations (i.e., top five citing countries) by technology field and country in the first and second periods. First, the top five patent citing countries in mature renewable technologies include Switzerland, Germany, the US, the UK, and Japan in the early period, but Japan was replaced by Korea in the latter period. Second, the top five patent citing countries in fossil-based has not changed from the early and latter periods of the study.

3.2. Estimation results

Table 3 shows the results of estimation of equation (1) for mature renewable energy and efficient fossil-based technologies over the full sample period (columns 1 and 2) and for the different sub-periods (columns 3 to 6). Compared to the pooled estimation of both

Table 2
Summary statistics.

Variable [unit]	Observation	Mean	Std. Dev.	Min	Max
No. of citations [#]	841	203	1032	0.00	25,224
Crossing country border [index]	841	0.97	0.18	0.00	1.00
Country distances [1000 km]	841	4.80	4.51	0.00	18.06
Crossing linguistic border [index]	841	0.89	0.31	0.00	1.00
Crossing trade border [index]	841	0.78	0.33	0.00	1.00
Crossing technological distance [index]	841	0.27	0.21	0.00	0.90
Vicinity of citing to the frontier of cited [index]	841	0.09	0.46	-0.74	2.80
Environmental policy stringency distance [index]	841	0.12	0.09	0.00	0.45



Notes: Country names and two-letter codes by Patent Cooperation Treaty (PCT) applicant's guide. A list of countries: US (United States), DE (Germany), CH (Switzerland), JP (Japan), FR (France), DK (Denmark), GB (United Kingdom), KR (Republic of Korea)

Fig. 3. Share of citations by country for mature renewables (upper panels) and fossil-based (lower panels) technologies, 1990–2002 (left) and 2003–2015 (right) Notes: Country names and two-letter codes by Patent Cooperation Treaty (PCT) applicant's guide. A list of countries: US (United States), DE (Germany), CH (Switzerland), JP (Japan), FR (France), DK (Denmark), GB (United Kingdom), KR (Republic of Korea).

Table 3

Barriers to knowledge diffusion in mature renewable technologies and fossil-based technologies, 1990–2015.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Full period		1990–2002		2003–2015	
	Mature renewables	Fossil-based	Mature renewables	Fossil-based	Mature renewables	Fossil-based
Crossing country border	–1.238*** (0.130)	–1.186*** (0.188)	–1.488*** (0.252)	–0.697*** (0.248)	–1.185*** (0.132)	–1.165*** (0.195)
Country distance	–0.014** (0.007)	–0.031** (0.013)	–0.033* (0.018)	–0.028 (0.023)	–0.011 (0.007)	–0.031** (0.013)
Crossing linguistic border	–0.086 (0.070)	–0.277*** (0.105)	–0.014 (0.142)	–0.251* (0.150)	–0.081 (0.071)	–0.280** (0.111)
Crossing trade border	0.058 (0.047)	0.005 (0.146)	0.108 (0.097)	0.056 (0.198)	0.017 (0.045)	0.049 (0.144)
Crossing technological distance	–1.402*** (0.155)	–0.851*** (0.286)	–0.808*** (0.290)	–0.945*** (0.312)	–1.452*** (0.158)	–0.917*** (0.311)
Vicinity of citing to frontier of cited	–1.454*** (0.288)	0.900 (0.695)	–0.025 (0.085)	0.181 (0.144)	–1.616*** (0.312)	0.609 (0.834)
Constant	3.621*** (0.151)	0.357 (0.314)	1.605*** (0.311)	–2.975*** (0.726)	3.532*** (0.155)	0.230 (0.330)
Observations	841	841	841	841	841	841
Citing country FE	YES	YES	YES	YES	YES	YES
Cited country FE	YES	YES	YES	YES	YES	YES

Notes: This table displays the estimation results of barriers to knowledge diffusion in mature renewables and fossil-based technologies, 1990–2015. Dependent variable: all citations within 5-year window from cited country j to citing country i . We measure the number of patent citations received by patents invented in climate mitigation technology fields (Table A1) from patents invented in mature renewables or fossil-based technologies. We re-constructed three independent variables (crossing trade border, crossing technological distance, and vicinity of citing to frontier of cited) to meet the given time period, respectively. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

technologies shown in Table B1 technology-specific patterns emerge.

Crossing a country border is a barrier to knowledge flow for both sets of technologies, albeit with different magnitude. Over the whole sample period, citation between two countries sharing a border is 29% ($e^{-1.238}$) as likely as citation to domestic patents for mature renewable technologies. The corresponding value for fossil-based technologies is 31% ($e^{-1.186}$). In our case, the coefficient associated with crossing a country border is smaller than in Ref. [3], potentially indicating that the role of geographical barriers has decreased over time—as is the case for the trade literature [38]. Differently from Ref. [3], additional geographical distance behind the crossing of a country border hinders further knowledge flows: citing a country that is 4800 km away—the average distance in our sample—is 50% as likely as citing a neighboring country.

Linguistic difference is a barrier to knowledge flow only in the case of fossil-based technologies: a citation between two countries which do not have the same official languages is 76% ($e^{-0.277}$) as likely as a citation between countries in the same official languages. Linguistic barriers are not associated with lower citation probabilities in the case of mature renewable technologies.

Trade barriers, on the other hand, are not associated with lower knowledge flows in either technology. This is different from what [3] found in the much earlier period (1975–2000), but in line with evidence of a persistent decline in trade barriers between 2000 and 2014 [38].

Knowledge flows are more likely among countries whose innovation activities are similar, but technological distance represents a higher barrier in the case of mature renewable technologies. Over the sample period, citations between two countries with completely different mature renewable innovation profiles are about 25% ($e^{-1.402}$) as likely as between two countries with the same mature renewable technological profile. The corresponding value for fossil-based technologies is 43% ($e^{-0.851}$). Focusing on the two subperiods, results are generally similar for fossil-based technologies—39% ($e^{-0.945}$) and 40% ($e^{-0.917}$). Conversely, in the case of mature renewable technologies, citations between countries with completely different technological profiles are 23% ($e^{-1.452}$) and 45% ($e^{-0.808}$) as likely as those between two identical countries for the first and second period, respectively. With respect to the variable measuring technological development ($x_{6(i,j)}$), we note that

the coefficient is significant, and negative, only in the case of mature renewable technologies for the full-period and the second sub-period.

Table 4 displays the estimation results for mature renewables and fossil-based technologies including environmental policy stringency distance for the full period and the two subperiods. First, the coefficient associated with this variable over the whole sample period is not statistically different from zero for either technology. This implies that distance in the environmental policy space does not hinder the likelihood of citation. However, note that the coefficient associated with this variable in the mature renewables model for the first time period is negative and significant, providing some albeit weak evidence that in the early years' policy distance may have represented a barrier to knowledge diffusion.

3.3. Inter-temporal heat maps

We use the coefficients in Table 3 to generate matrixes of knowledge diffusion parameters for mature renewables and fossil-based technologies over the two periods of time 1990–2002 and 2003–2015 in our sample countries (Equation (5)). These heat maps visually illustrate the results from our empirical estimation. Citing countries, i.e., the countries receiving the knowledge, are listed in the rows, while cited country, i.e., the country source of knowledge, are listed in the columns. Note that the underlying data, i.e., the estimated shares of knowledge flowing between sending and receiving country in the two sample periods, is provided in Table B.2-5 in the Appendix. These can be fruitfully used to calibrate knowledge production functions in a wide range of models for integrated assessment of the energy, the economy and the climate.

These heat maps should be interpreted keeping in mind that the diagonal entry is equal to 1 by construction, as previously explained. That is, the heat maps allow us to compare the intensity of the international knowledge received by the citing country as compared to the own knowledge it produces and builds upon. Also note that by construction, the estimated knowledge diffusion parameters are asymmetric, i.e., the intensity of knowledge flows between two countries differs depending on the direction of knowledge flow.

A few key insights emerge. First, in the earlier period, the intensity of

Table 4

Barriers to knowledge diffusion in mature renewables and fossil-based technologies including environmental policy distance, 1990–2011.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Full period		1990–2000		2001–2011	
	Mature renewables	Fossil-based	Mature renewables	Fossil-based	Mature renewables	Fossil-based
Crossing country border	−1.061*** (0.133)	−1.387*** (0.219)	−0.887*** (0.281)	−0.944*** (0.344)	−1.062*** (0.132)	−1.483*** (0.231)
Country distance	−0.024*** (0.008)	−0.039*** (0.015)	−0.025 (0.018)	−0.053* (0.028)	−0.022*** (0.007)	−0.031** (0.016)
Crossing linguistic border	−0.028 (0.071)	−0.215* (0.118)	−0.274* (0.154)	−0.440** (0.183)	−0.023 (0.071)	−0.161 (0.129)
Crossing trade border	0.020 (0.048)	0.204 (0.166)	0.301*** (0.111)	0.311 (0.249)	−0.001 (0.047)	0.200 (0.174)
Crossing technological distance	−1.687*** (0.164)	−0.820*** (0.306)	−1.932*** (0.328)	−0.295 (0.364)	−1.696*** (0.165)	−0.688** (0.339)
Vicinity of citing to frontier of cited	−1.773*** (0.399)	1.114 (0.985)	−0.025 (0.094)	0.001 (0.133)	−1.964*** (0.444)	0.027 (1.289)
Environmental policy distance	−0.398 (0.291)	0.143 (0.571)	−0.946* (0.527)	−0.154 (0.689)	−0.374 (0.253)	0.576 (0.551)
Constant	3.256*** (0.154)	−0.020 (0.368)	0.848** (0.346)	−1.136** (0.558)	3.217*** (0.156)	−0.653 (0.428)
Observations	841	841	841	841	841	841
Citing country FE	YES	YES	YES	YES	YES	YES
Cited country FE	YES	YES	YES	YES	YES	YES

Notes: This table displays the estimation results of barriers to knowledge diffusion in mature renewables and fossil-based technologies, 1990–2011. Dependent variable: all citations within 5-year window from cited country j to citing country i . We measure the number of patent citations received by patents invented in climate mitigation technology fields (Table A1) from patents invented in mature renewables or fossil-based technologies. We re-constructed four independent variables (crossing trade border, crossing technological distance, vicinity of citing to the frontier of cited, and environmental policy distance) to meet the given time period, respectively. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

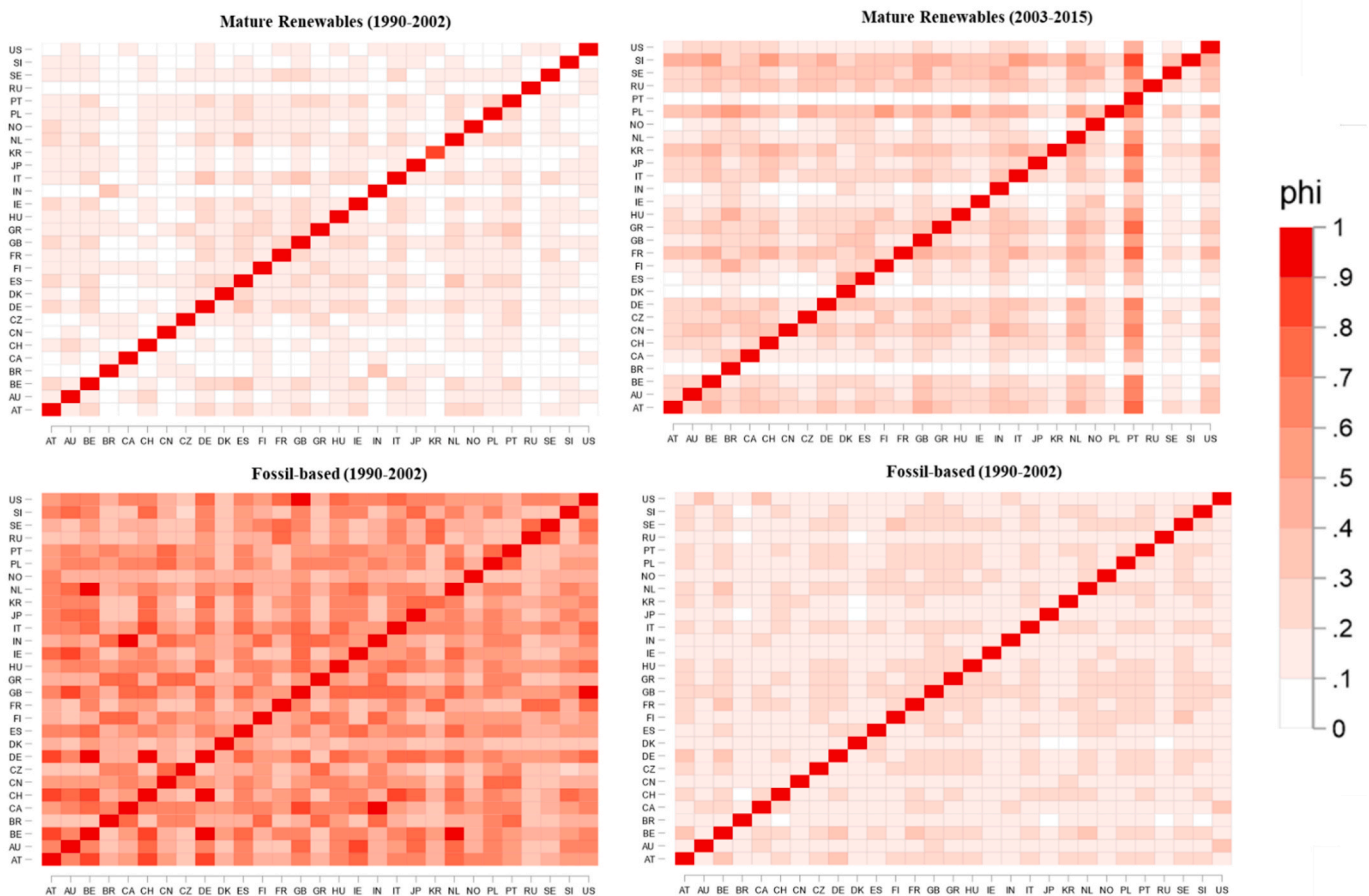
international knowledge flows in efficient fossil-based technologies relative to domestic knowledge flows was higher than for mature renewable technologies. For mature renewable technologies, domestic knowledge flows were much more intense (i.e., the cells are of a darker shade) than knowledge flows from abroad (Fig. 4), which were practically inexistent. Second, a very different picture emerges for the second period. On the one hand, the average relative intensity of international knowledge flows relative to that of domestic knowledge flows is higher for mature renewable technologies, including for those countries which did not benefit from knowledge spillovers in the earlier period. On the other hand, the opposite is true for fossil-based technologies: the relative intensity of international knowledge flows decreased as compared to domestic knowledge flows. This indicates that all countries in our sample rely less on international knowledge to foster domestic innovation as compared to the previous period.

4. Conclusion

This paper estimates the role of barriers to knowledge diffusion in

mature renewables and fossil-based technologies in a sample of 29 countries—including fast-growing economies—over the period 1990–2015. Our results provide a more nuanced picture than previous analyses. First, we show that geographical barriers hinder knowledge diffusion in both mature renewable and fossil-based technologies, but their role increases over time for former and not for the latter. Second, language is a barrier for knowledge flows only in the case of fossil-based technologies. Third, trade barriers do not appear to hinder knowledge flows in our sample. We show that knowledge flows are higher in countries with similar technological profiles. This is particularly true for mature renewable technologies. Our analysis does not support the conjecture that distance in policy space reduces the probability of knowledge flows.

We use our empirical results to generate knowledge spillover parameters across countries for 1990–2002 and 2003–2015. These parameters further illustrate that international knowledge spillovers increased in intensity as compared to domestic spillovers for mature renewable technologies in the second half of the sample period. This is true in most countries in our sample, including those which showed no



Notes: Raw data is provided in Table B.2-5 in the appendix. Self-citations (citations to the same assignee) are excluded. Country names and two-letter codes by Patent Cooperation Treaty (PCT) applicant's guide. A list of countries: AT (Austria), AU (Australia), BE (Belgium), BR (Brazil), CA (Canada), CH (Switzerland), CN (China), CZ (Czech Republic), DE (Germany), DK (Denmark), ES (Spain), FI (Finland), FR (France), GB (United Kingdom), GR (Greece), HU (Hungary), IE (Ireland), IN (India), IT (Italy), JP (Japan), KR (Republic of Korea), NL (Netherlands), NO (Norway), PL (Poland), PT (Portugal), RU (Russia), SE (Sweden), SI (Slovenia), US (United States)

Fig. 4. Estimated diffusion parameters for mature renewables (upper panels) and fossil-based (lower panel) technologies, 1990–2002 (left) and 2003–2015 (right) **Notes:** Raw data is provided in Table B.2-5 in the appendix. Self-citations (citations to the same assignee) are excluded. Country names and two-letter codes by Patent Cooperation Treaty (PCT) applicant's guide. A list of countries: AT (Austria), AU (Australia), BE (Belgium), BR (Brazil), CA (Canada), CH (Switzerland), CN (China), CZ (Czech Republic), DE (Germany), DK (Denmark), ES (Spain), FI (Finland), FR (France), GB (United Kingdom), GR (Greece), HU (Hungary), IE (Ireland), IN (India), IT (Italy), JP (Japan), KR (Republic of Korea), NL (Netherlands), NO (Norway), PL (Poland), PT (Portugal), RU (Russia), SE (Sweden), SI (Slovenia), US (United States).

benefits from international knowledge flows in the first half of the sample. The opposite is true for fossil-based technologies.

Our findings confirm that knowledge spillovers have technology-specific dynamics, and that they are not static over time. Note that the estimated diffusion parameters for foreign knowledge to any country in our sample increased over time, particularly over the last decades in mature renewable technologies. Overall, this is consistent with the hypothesis that domestic knowledge contributes to generating further knowledge also in foreign countries, ultimately increasing our decarbonisation options and lowering the costs associated with mitigation. Ignoring this fact in the generation of mitigation scenarios would lead to an underestimation of the benefits associated with innovation as well as to an overestimation of the costs associated with mitigating climate change. Conversely, low-decarbonisation pathways should account for these specificities. A fruitful avenue of further research lies in the use of our estimated diffusion parameters for the calibration of integrated assessment knowledge with endogenous, country- or region-specific knowledge production functions.

Our paper also points to other interesting future research avenues. These include the need to further explore distance in the policy space as a potential factor hindering knowledge flows, as well as the careful estimation of cross-technology knowledge flows. This latter part is particularly important with respect to cross-technology spillover effect in the learning process of a country might hinder cross-country knowledge spillovers. Cross-technology knowledge flows are also important with respect to digital technologies, and the role they are bound to play in the further development of energy technologies for effective mitigation. Furthermore, the future research avenue also includes the link between knowledge spillovers and cost reductions in low-carbon technologies.

As any study, our paper has a few caveats. First, our set up ignores cross-country collaborations as an important avenue of knowledge spillovers, as we rely on citation counts but do not explore patents which are jointly filed by inventors in different countries. We leave this for further future analyses. Second, environmental policy distance is a newly proposed index in this paper, but there is room for improvement. Third, we consider only two sets of technology fields to compare which warrants the necessity of the more granular level of analysis including the rest of the distinct technology field (e.g., nuclear).

Credit author statement

Yeong Jae Kim: Conceptualization, Methodology, Software, Data curation, Investigation, Visualization, Writing – original draft, Writing-Reviewing and Editing, **Elena Verdolini:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing- Reviewing and Editing

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that have influenced the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.esr.2023.101151>.

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