



MACROECONOMIC MODELLING OF R&D FOR THE TWIN TRANSITION

D3.1 | Innovation, energy and green technologies in GEM-E3

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List of Acronyms and Abbreviations

lbd	Learning by doing
lbr	Learning by research
lr	Learning rates
CGE	Computable General Equilibrium model
EU27/EU	European Union – 27 members



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Introduction

Achieving Net Zero is not simply a matter of deploying the technologies we already have; it requires a profound transformation of industrial systems, energy infrastructures, and consumption behaviours. At the centre of this transformation lies Research and Development (R&D)—the engine that turns climate ambition into scalable, market-ready solutions. Breakthroughs in high-density energy storage, green hydrogen, advanced materials, carbon capture, and circular bio-economy processes all depend on sustained and targeted R&D efforts. Without continuous innovation, the cost and performance improvements needed for a rapid decarbonization pathway would stall.

The concept of “Twin R&D” highlights the dual and interconnected nature of the green and digital transitions. The Green Transition focuses on decarbonizing energy, transport, and industry, while the Digital Transition provides the intelligence, optimization, and system-level coordination required to operate increasingly complex and decentralized energy systems. When digitalization is embedded within a green-energy context, it amplifies socio-economic benefits: faster innovation cycles, enhanced competitiveness of clean-tech industries, and improved quality of life in urban environments. Technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and advanced analytics are indispensable for managing renewable-dominated grids, optimizing energy storage, and enabling real-time demand response. In this sense, digital R&D is not optional—it is a prerequisite for an efficient and affordable green transition.

Yet the Twin Transition also introduces new risks that can undermine decarbonization efforts if not properly managed. The most immediate challenge is the energy intensity of digital infrastructure. As Europe expands its use of AI, high-performance computing, and large-scale data centres to support smart systems, electricity demand rises sharply. If this digital expansion outpaces the deployment of additional renewable capacity, the Twin Transition risks becoming a zero-sum game, where efficiency gains are offset by the carbon footprint of the digital backbone itself. Beyond energy use, the digital transition intensifies pressures on Critical Raw Materials (CRMs) such as lithium, cobalt, and rare earth elements—materials essential for both digital hardware and green technologies like batteries, electric vehicles, and wind turbines. Competition for these finite resources, combined with short hardware lifecycles and growing e-waste, creates a structural tension between the two transitions that must be addressed through innovation, recycling, and strategic resource policies.

At the heart of this broader transformation is the European Green Deal’s commitment to making Europe the first climate-neutral continent by 2050. As we move through 2026, it is increasingly clear that incremental progress is insufficient. Bridging the gap between current emissions trajectories and the Net Zero target requires fully harnessing the synergistic potential of the Twin Transition, where green and digital innovation reinforce each other rather than compete.



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The TWINRD projects aims to provide a quantitative assessment of the TWIN transition by updating and upgrading existing modelling tools and developing a specifically designed economic model for this purpose. This deliverable presents the extension of the GEM-E3 model to capture learning effects stemming from R&D, with a special focus on green energy and equipment sectors. The structure of the report is as follows: Section 1 describes the R&D module included in the GEM-E3 model and data sources used for calibration, Section 2 presents a quantitative assessment of a decarbonization scenario with and without learning by research, Section 3 presents the Quasi Monte Carlo methodology for assessing uncertainty in a CGE framework and its application in the GEM-E3 model and Section 4 concludes and provides guidelines for future research.

1. Methodology

This chapter provides an overview of the R&D modelling in the GEM-E3 model as well as a description of the main data that are required for the calibration and the operation of the R&D module. The R&D module of GEM-E3 is developed with a special focus on green energy technologies. The model individually represents sectors producing batteries, electric vehicles, electrolyzers, solar PV modules, wind turbines etc. Our main objective is to capture dynamics associated with production cost developments in emerging technologies (e.g. hydrogen, clean fuels) that determines largely the overall cost of the transition.

The introduction of learning by research which is linked to public and private R&D expenditures is a central mechanism through which the impacts of innovation and its diffusion of innovation (i.e. the way technological advances developed in one region or sector are adopted by others, translating into productivity improvements) are captured. Knowledge spillover reflects the empirical reality that innovation does not remain confined within national or sectoral boundaries: patented knowledge generated through research and inventive activity diffuses across the economy, enabling firms, sectors, and regions to build upon discoveries originating elsewhere.

1.1. GEM-E3 model

GEM-E3 is a global, multi-sector, multi-regional recursive dynamic CGE model with worldwide coverage. It is formulated as a system of simultaneous equations derived from the optimizing behaviour of economic agents—firms and households. The model represents supply and demand decisions using market-clearing prices, enabling a consistent assessment of the distributional effects of policies. Economic dynamics are driven by capital accumulation, while the model also features involuntary unemployment, energy-efficiency standards, and carbon pricing. Across all scenarios, the economic system remains in general equilibrium. All agents behave as price takers under perfect competition. Representative firms produce a single homogeneous good per sector and minimize costs by combining capital, labour, and intermediate inputs according to a nested Constant Elasticity of Substitution (CES) production



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structure. Households maximize Stone-Geary utility subject to a budget constraint, receiving income from labour and from ownership of firms. Sectoral investment evolves dynamically based on adaptive expectations regarding capital returns and activity growth. Private consumption is allocated across COICOP categories and translated into demand for specific goods through a fixed-coefficient consumption matrix. Bilateral trade follows the Armington assumption, treating goods from different origins as imperfect substitutes.

Labour market imperfections are introduced through a Phillips curve linking wages and unemployment, allowing the model to generate equilibrium unemployment. Capital is mobile across sectors, and its accumulation is determined by investment decisions that depend on capital rents, expectations of future demand, investment costs, and interest rates. Agents are assumed to be myopic. The model includes 51 production sectors, and labour is differentiated into five occupational categories.

The model's national database draws on Eurostat (National Accounts, Public Finance, Input-Output tables, Labour statistics), WIOD, and GTAP. A dedicated calibration routine computes the scale parameters of production and consumption functions to ensure that the model reproduces base-year statistics exactly. GEM-E3 projects the full structure of production, consumption, and market equilibrium for all sectors and regions. Population is treated as exogenous, with projections based on the 2019 Ageing Report.

GEM-E3 includes a detailed representation of the energy system. The electricity sector is modelled bottom-up, with 12 distinct power-generation technologies represented as separate production sectors. Passenger and freight transport are also modelled bottom-up, incorporating choices between transport modes and technologies and the associated use of transport equipment. Household energy use is explicitly represented, including heat pumps and electric appliances, and depends on household income and the cost of purchasing and operating energy equipment. This detailed energy representation enables consistent estimation of emissions and mitigation pathways, including fuel substitution (covering fossil fuels, renewable electricity, biofuels, and hydrogen) and energy-efficiency improvements through investment in more efficient equipment. Beyond energy-related emissions, the model captures all non-energy and non-CO₂ greenhouse gases and includes end-of-pipe abatement options via bottom-up marginal abatement cost curves (MACCs) differentiated by country, sector, and pollutant.

To support a robust assessment of the macroeconomic implications of the low-carbon transition, GEM-E3 also explicitly represents the manufacturing of clean-energy equipment as dedicated production sectors, including PV panels, wind turbines, electric vehicles, EV batteries, biofuels, and hydrogen. Supplementary sectoral data sources are used to estimate market size, structure, and trade flows for these industries.



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1.2. R&D expenditures and Learning by research in GEM-E3

1.2.1. Mathematical formulation

The R&D module is based on the model extension that was developed under the MONROE Horizon project¹. R&D expenditures by firms and governments build the country specific knowledge stock based on which the productivity associated with learning by research is calculated. It is assumed that knowledge stock deteriorates over time (2), reflecting the necessity to continuously invest in R&D to stay up to date to global developments.

R&D expenditures are semi-endogenous in the GEM-E3 model, meaning that they are determined endogenously in the model but there is no feedback loop between the decision to invest in R&D and the associated productivity gains.

$\text{PrivateRD}_{i,c,t} = f(\theta_{rnd,i,c,t}, XD_{i,c,t})$	(1)
--	-----

$\text{CumulativePrivateRD}_{i,c,t} = \text{CumulativePrivateRD}_{i,c,t-1} \cdot (1 - dk) + \text{PrivateRD}_{i,c,t}$	(2)
---	-----

$\text{tfpPrivateRD}_{i,c,t} = \left(\frac{\text{CumulativePrivateRD}_{i,c,t}}{\text{CumulativePrivateRD}_{i,c,t-1}} \right)^{lr_i}$	(3)
---	-----

$\text{PublicRD}_{i,c,t} = f(\theta_{rnd,i,c,t}^{gov}, XD_{i,c,t})$	(4)
---	-----

$\text{CumulativePublicRD}_{i,c,t} = \text{CumulativePublicRD}_{i,c,t-1} \cdot (1 - dk) + \text{PublicRD}_{i,c,t}$	(5)
--	-----

$\text{tfpPublicRD}_{i,c,t} = \left(\frac{\text{CumulativePublicRD}_{i,c,t}}{\text{CumulativePublicRD}_{i,c,t-1}} \right)^{lr_i}$	(6)
--	-----

Set	Description
i	Sectors
c	Countries
t	time
Parameters	Description

¹ MONROE - Modelling and evaluating the socioeconomic impacts of research and innovation with the suite of macro- and regional-economic models (grant agreement No 727114)



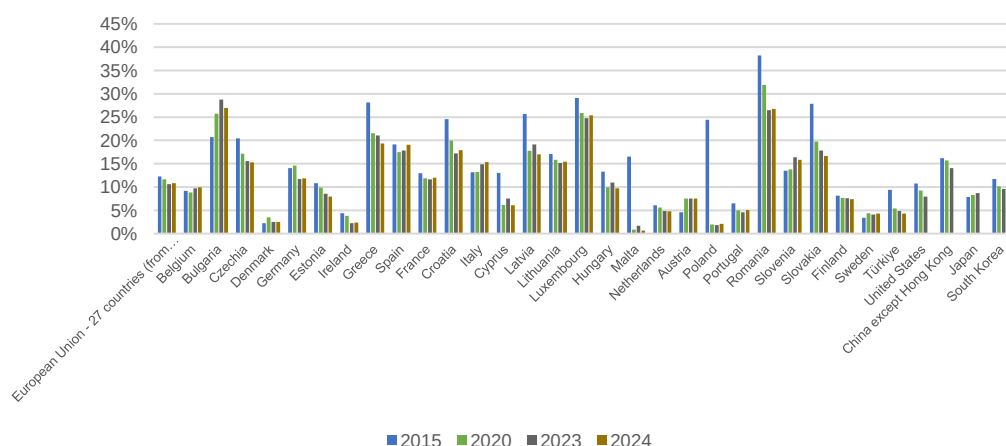
$\text{PrivateRD}_{i,c,t}$	R&D expenditures
Variables	Description
$\theta_{rnd,i,c,t}$	Value share of R&D in the production of sector i
$XD_{i,c,t}$	Production of sector i

1.2.2. R&D expenditures and learning rates

For the calibration of knowledge stock and R&D expenditures by sector we combine data from 3 different sources: OECD and Eurostat regarding total R&D expenditure by agent (public, private), IEA (for green energy technologies) and ANBERD (for the rest of the industries). The first two sources are used to calculate government spending in the R&D for green energy sectors². The ANBERD database is used for updating the R&D value shares³ in the sectoral production function.

Public R&D investment currently accounts for approximately 10% of total national R&D expenditure across major global economies, though its growth has lagged compared to that of private investments. Within the EU-27, public R&D has remained relatively stagnant as a percentage of GDP over the last 15 years (0.24% of GDP approximately). However, this average mask significant divergence at the Member State level; several countries consistently maintain high public R&D spending, exceeding 15% of their total research outlays (e.g., Greece, Spain, Bulgaria). Critically, when compared to the United States and China, the EU is losing ground, with the investment gap widening progressively since 2015.

Figure 1: Public investments as % of total Investments for selected countries



Source: Eurostat⁴

² The IEA dataset includes 4 different categories: renewables, hydrogen and fuel cells, energy efficiency, cross-cutting technologies.

³ The value of R&D expenditures by sector as percentage of total production

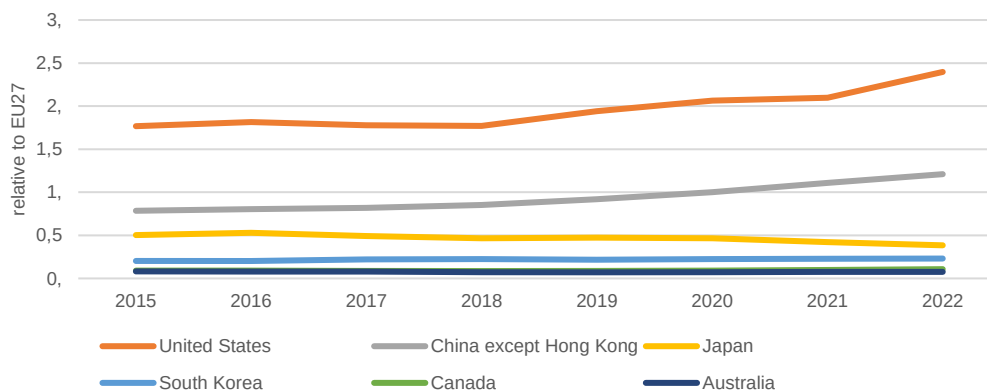
⁴ https://doi.org/10.2908/RD_E_GERDTOT



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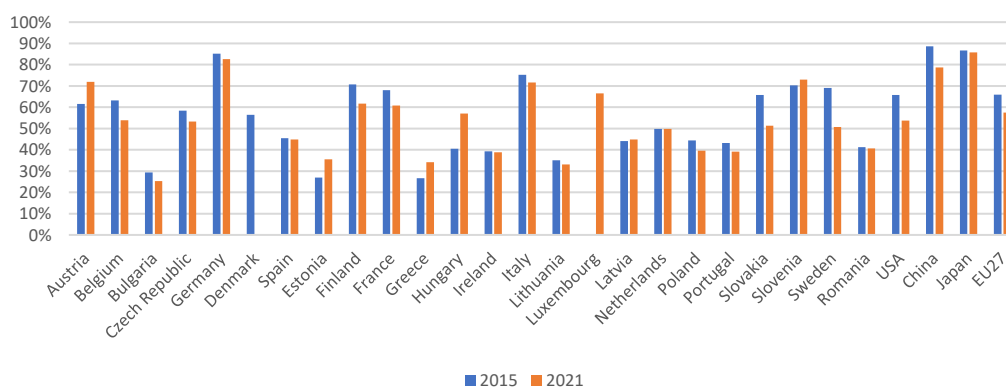
Figure 2: Total R&D investments of selected major economies - relative to EU27



Source: Eurostat, OECD⁵

Manufacturing remains the primary driver of R&D investment, accounting for over 50% of total economic expenditure on research and development. However, manufacturing consistently claims over 50% of total R&D resources, the sectoral distribution varies by region. For example, in the EU-27's R&D profile is heavily weighted toward transport equipment (approx. 14%), whereas the manufacturing of computers and electronics constitutes the largest R&D share in China, the USA, and Japan.

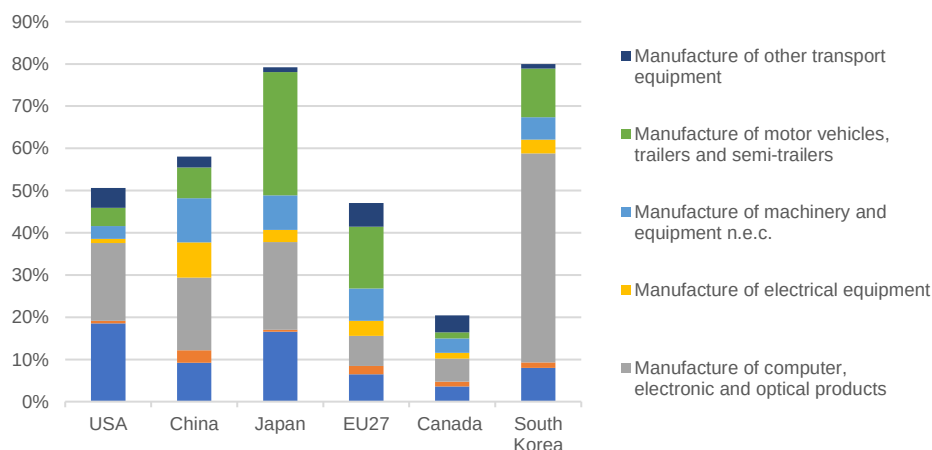
Figure 3: R&D expenditures in manufacturing sectors - % of total RD expenditures



Source: ANBERD database

⁵ (OECDCS1) Topic: (INT) Science, technology and innovation > (INT_RD) Research and development (R&D)
>(DSD_RDS_GERD@DF_GERD_TORD) Gross domestic expenditure on R&D by sector of performance and type of R&D

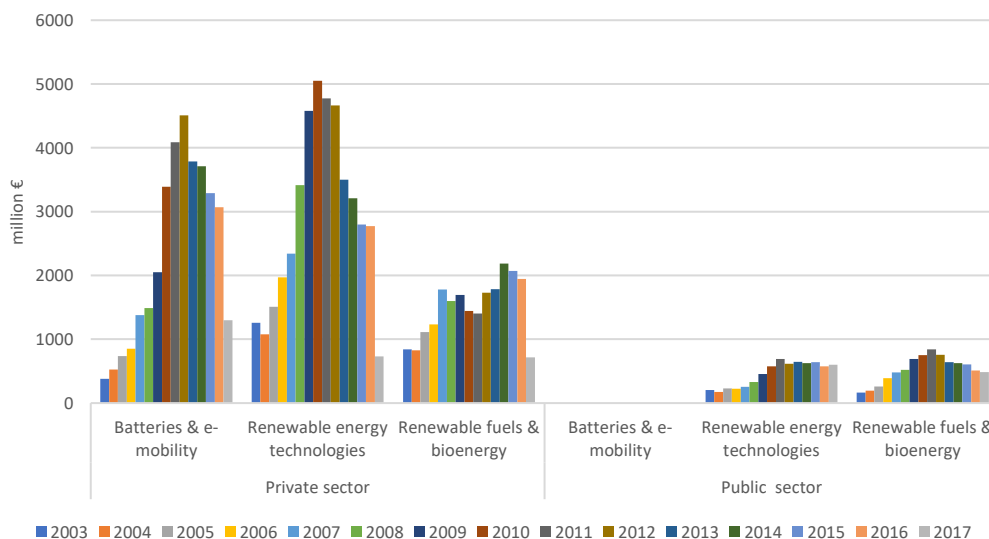
Figure 4: R&D expenditures in selected manufacturing industries - % in total



Source: ANBERD database

Public R&D spending on green initiatives shows a nearly equal split between renewable power technologies and bioenergy, as reported by the SETIS Innovation and Research Scoreboard. Despite this steady public backing, the broader investment landscape faces challenges, with total private expenditures in the green energy sector currently trending downward.

Figure 5: Public R&D expenditures by type



Source: SETIS R&I country dashboards

With respect to clean energy technologies, and more specifically batteries, manufacturing of solar PV module, manufacturing wind equipment, electrolyzers and heat pumps, the original model database has been revised based on publicly available market data and reports.



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Table 1: R&D expenditures as % of total revenues

Sector	Range
Electrolyzers	6%-15%
Solar PV	3.6%-6%
Wind turbines	5%
Batteries	6%-10%

Source: author's calculations

The update of the model's R&D database is essential for the robust calibration of the knowledge stock which is essential for the scenario assessment (as it influences future productivity effects) and to ensure consistency of model's overall R&D expenditures with published data⁶ at the country level as well as the R&D intensity by sector. Furthermore, the update of R&D expenditures of non-green sectors allows the model to consistently capture the impact of cross-sectoral spillovers. For future modelling periods (i.e. after 2025), relative R&D spending⁷ by sector is assumed to remain constant and set equal to the latest available publication year⁸.

With respect to learning rates, most of the published research refers to learning-by-doing (lbd) effect, estimated through a One Factor Learning Curve (OFLC) where cost reductions are associated with the expansion of installed capacity. Fewer studies expand their scope to estimate also the role R&D (lbr) applying a Two Factor Learning Curve (TFLC), while lately there are studies that disaggregate overall productivity gains by input using multi-factor curves (MFLC). However, it is difficult to trace the contribution of R&D to the relative cost reduction of sub-components in multi-factor curves. In overall, the literature gives mixed results, with estimated learning rates varying significantly per study as it depends on the type of data used, the time period, current and projected energy costs etc. Table 1 presents the most recent literature on the learning rates by type. For the GEM-E3 model we have selected middle-of-the-road values for the sectors of interest that lie within the ranges provided by the literature:

Table 2: Review of learning rates

Sector ⁹	LBD	LBR	MFLC	Other modelling techniques, qualitative assessments	Learning rates assumed in GEM-E3
Heat pumps	3.3%-5% ¹⁰				5%

⁶ For countries that have no records we assume that they follow the global average structure

⁷ As % of total production

⁸ 2022 for most of the countries in the model

⁹ For PV and Wind equipment most of the relevant studies refer to the respective power generation technology and not the manufacturing segment

¹⁰ Renaldi et al., 2021



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Equipment for wind	13%	10% ¹¹ 16.5% ¹² 33% ¹³ 2%-15% ¹⁴ 7%-9% ¹⁵ 37% ¹⁶ 14% ¹⁷ 4.9%(offshore) - 16.5% (onshore) ¹⁸		4%-12% ¹⁹ (contribution to overall cost reduction)	10%
Equipment for PV panels	18% (footnote 13)	35%-58% ²⁰ 10% 12% ²¹ 18% ²² 66%-75% ²³	24%-26% (same as CCS study)	R&D contributing to 60% in cost reduction ²⁴ (lbr ~ 12.5%)	15%
Equipment for CCS power technology, CO2 capture ²⁵	10%-15% ²⁶ , 18%-20% ²⁷ (implied)	10%	4.9%-19.9% ²⁸	11%-15% ²⁹ (ranging from 9%-18%)	10%
Batteries		20%-27% ³⁰ , 31.4% ³¹		R&D responsible for 54% of the observed cost reduction ³²	10%
Electrolyzers	5-18% ³³ (by component) 18±13% ³⁴ 9-13% ³⁵ 9% ³⁶	0-24% (lbr) ³⁷	13.8-15% ³⁸		10%

¹¹ Wiesenthal et al., 2009¹² Rubin et al., 2015¹³ Wiser et al., 2020¹⁴ Odam and de Vries, 2020¹⁵ Schauf and Schwenen, 2022¹⁶ Zhou and Gu, 2019¹⁷ Kobos et al., 2006¹⁸ Rubin et al., 2015¹⁹ Wiser et al., 2018²⁰ Ding et al., 2020²¹ Rubin et al., 2015²² Kobos et al., 2006²³ Zhou and Gu, 2019²⁴ Kavlak et al., 2018²⁵ In the GEM-E3 model these sectors refer to similar technologies. One is linked to the production of clean gas (CO2 capture) and the other with the supply of the relevant equipment in power generation sectors²⁶ Fasihi et al., 2019²⁷ ClimateXChange, 2025²⁸ Wei et al., 2025²⁹ Sievert et al., 2024³⁰ Mayer et al., 2012³¹ Kittner et al., 2017³² Ziegler et al., 2021³³ IRENA, 2020³⁴ Schroots et al., 2008³⁵ Hydrogen Council, 2020³⁶ Detz and Weeda, 2022³⁷ Schmidt et al., 2017³⁸ Wang et al., 2026

1.3. Spillover effects in GEM-E3

The objective of this section is to describe the methodology used to construct a diffusion of innovation table (sometimes referred to as a ‘spillover table’) that quantifies these cross regional and cross sectoral flows of patented technological knowledge. The approach is fully data driven and relies on the methodology of Nomaler & Verspagen, 2025 including the comprehensive datasets of patent family counts and knowledge flow indicators (United Nations University – Maastricht Economic and Social Research Institute on Innovation and Technology [UNU-MERIT], 2025) containing detailed information on patent citations and patent family counts. Patent citations serve as observable indicators of the direction and intensity of knowledge diffusion, since a patent citation explicitly links a new invention to prior patented technology. Patent family counts, in contrast, measure the innovative capacity of each region and sector, capturing the stock of patented inventions produced. Together, these datasets offer a coherent empirical foundation for estimating the extent to which patented technological advances in one part of the economic system support innovation elsewhere.

While patent family counts reveal the volume of patented innovations, they do not describe how these innovations diffuse across regions and sectors. The diffusion dimension is instead captured by the patent citation data, which identify the region–sector pairs whose patents are cited by others. To translate these citation flows into a meaningful proxy for the spread of patented knowledge, the methodology introduces a patent intensity metric, defined as the ratio between total patent families and total patent citations received in each region–sector. This metric links the stock of patented innovations to the observed frequency with which these innovations are cited. Applying patent intensity to the citation flow matrix allows citation flows to be converted into patent-weighted flows, approximating how patented knowledge moves across regions and sectors. The final innovation diffusion coefficient is then computed as the ratio between the patent-weighted flow from an origin region–sector to a destination region–sector and the total number of patents produced by the origin (the detailed steps to calculate the matrix are provided in the Annex). Under the modelling simplifying assumption that one patent corresponds to one unit of total factor productivity (TFP), this coefficient provides the mechanism through which learning by research effects are incorporated into GEME3.

$tfpSpillRD_{i,c,t} = \sum_{j,c2} DiffusionMatrix_{i,j,c1,c2} \cdot (tfpPrivateRD_{j,c2,t} - 1)$	(7)
--	-----

The resulting innovation diffusion table enables GEME3 to incorporate a transparent and empirically grounded representation of knowledge diffusion. By linking microlevel indicators derived from patent data with macroeconomic modelling requirements, this framework provides a realistic depiction of how patented technological progress spreads across the global economy and how research activities in one region–sector contribute to productivity growth elsewhere.



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1.4. Total R&D driven productivity in GEM-E3

Total R&D driven productivity is the product of all R&D subcomponents: learning effects attributed to R&D financed by firms, by government and the associated cross-country, cross-sectoral spillovers.

$tfpRD_{i,c,t} = (1 + (tfpPrivateRD_{i,c,t} - 1)) \cdot (1 + (tfpPublicRD_{i,c,t} - 1)) \cdot (1 + (tfpSpillRD_{i,c,t} - 1))$	(8)
---	-----

Total factor productivity leads to lower production costs. This in turn implies a price effect for consumers as now they spend less for any given quantity allowing them to increase consumption of other goods and services and yields welfare improvements. Furthermore, in the case of clean energy technologies this translates into higher competitiveness over fossil fuels and fossil-based equipment which may (depending on the overall learning effect) lead to higher adoption rates, accelerating decarbonization.

2. Scenario description and Results

This section illustrates the influence of endogenizing R&D driven productivity in the GEM-E3 model by comparing two alternative scenarios. The first scenario (Decarb_noRD) is a decarbonization scenario that assumes no endogenous technical growth. While the second scenario (Decarb_RD_GG) includes the module, described in the previous sections, which calculates endogenously the R&D driven productivity. This scenario setup considers knowledge flows only between green technologies (GG). We then extend our coverage by including knowledge transfers between other non-green industrial sectors and green sectors (Decarb_RD_AG).

Table 3: Scenario description

	Policy context	RD	Spillovers
Decarb_noRD	NETZERO (driven by carbon prices)	Exogenous	No
Decarb_RD_GG	NETZERO (carbon prices equal to noRD scenario)	Endogenous (green sectors)	Green to green sectors, country to country
Decarb_RD_AG	NETZERO (carbon prices equal to noRD scenario)	Endogenous (green sectors)	All to green sectors, Country to country

For the presentation of macroeconomic impacts, the three decarbonization scenarios are compared against a Reference scenario, unless stated otherwise. The Reference scenario is a “constructed” scenario, i.e., the model is calibrated to replicate available macroeconomic and demographic projections (as reported by IMF, DGEFIN, UN,ILO). This section includes



information on price developments, changes on GDP and changes in sectoral production, imports and exports of green energy goods and related equipment.

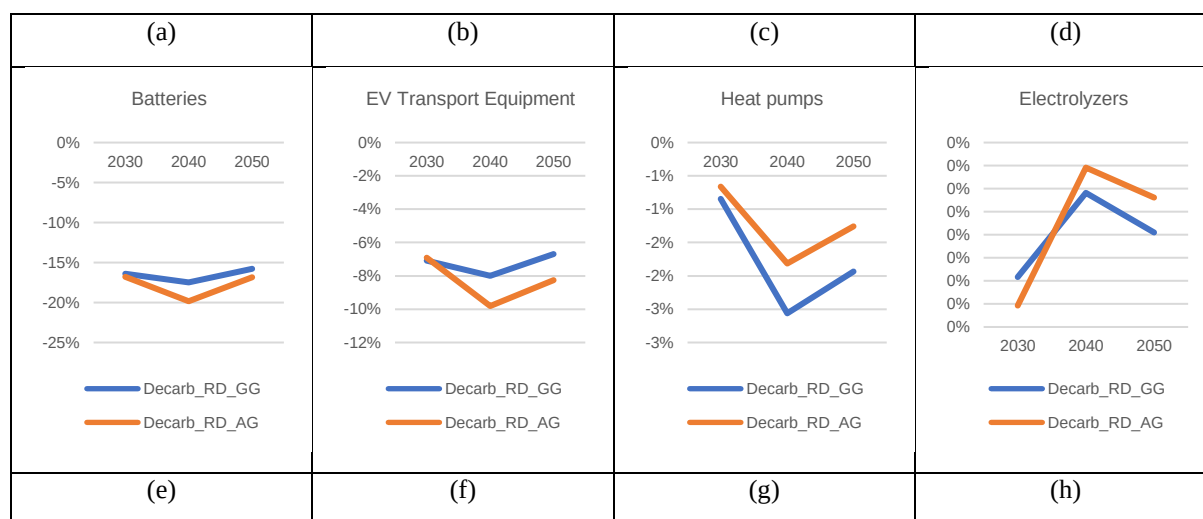
2.1. Impacts on clean energy and equipment prices

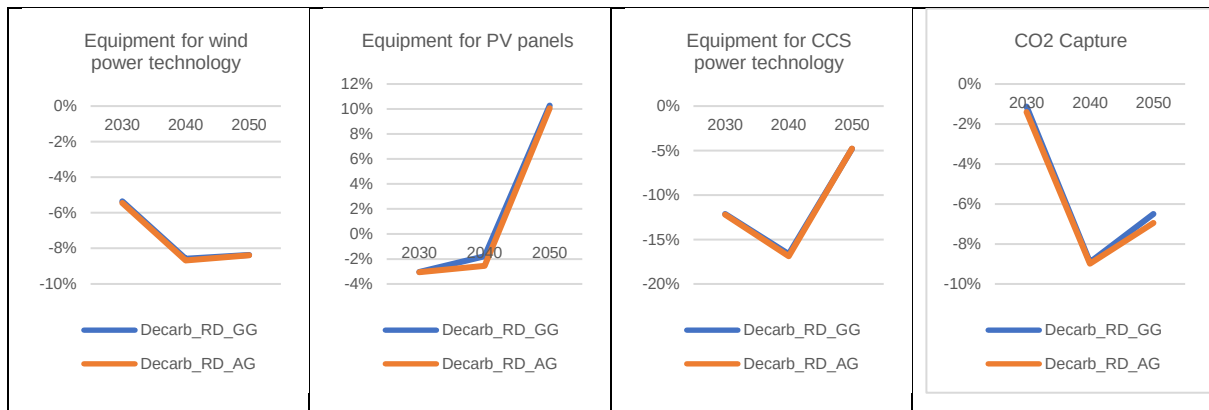
Cost dynamics for low-carbon technologies remain the primary determinant of the transition's macroeconomic impact. The synergy between R&D spending and increased productive capacity lowers the entry barrier for clean energy goods, directly challenging the dominance of fossil fuels. The analysis shows that at the aggregate level the price of clean energy goods (hydrogen, clean gas and biofuels) decreases up to 16%-17% in 2050 compared to the Decarb_noRD scenario and up to more than 40% compared to the reference scenario.

This price drop creates a substitution effect as the overall share of these fuels in the household energy mix increases by 3% on average in the EU-27. However, the impact is geographically varied, with Germany, France, Italy, and the Netherlands. The same substitution effect is found in industrial processes which shift towards hydrogen substituting fossil energy and clean gas.

With respect to clean energy related equipment, cost reductions are smaller compared to fuels. Significant drop in the cost of CC equipment is projected in both scenarios where compared to the Decarb_noRD case costs drop by more than 17% in 2050 and smaller changes, up to 4% are projected for heat pumps, PV and wind equipment. The latter relates to the projections on their sectoral activity as most of the required investments (hence demand) comes is realized up to 2030.

Figure 6: Production cost changes in clean energy manufacturing industries - % change from Decarb_noRD case





Source: GEM-E3

2.2. Macroeconomic impacts

At the macro level the introduction of R&D driven productivity has positive impact on the overall macroeconomic both at the EU and at the global level compared to the scenario version with no R&D learning effects. Productivity gains associated with higher R&D expenditures in green energy technologies and equipment reduces production costs lowering the overall costs of the transition (Figure 1). At the EU27 level, cumulative GDP losses, for the period 2025-2050, are found to be equal to 1.1% under the Decarb_noRD scenario (compared to the Reference), 0.8% under the Decarb_RD_GG scenario and 0.7% under the Decarb_RD_AG scenario.



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Figure 7: GDP changes in EU27 (a) and in the RoW (b) - % change from reference



Source: GEM-E3

Macroeconomic impacts of the clean energy transition are mainly driven by the exports channel as indicated in Figure 2. Carbon pricing, higher energy efficiency and less emission intensive processes result in a loss in competitiveness due to higher costs associated to fossil fuel consumption and higher capital (upfront) cost for the adoption of clean processes (in production) and equipment (in households and buildings).

Integrating R&D-induced productivity gains into the model, both private consumption and investment show a marked increase relative to the 'noRD' scenario. The declining cost of green energy carriers—specifically biofuels, hydrogen, and clean gas—accelerates their integration into the fuel mix, fostering an expansion in EU-27 production. Results indicate that, compared to the *Decarb_noRD* case, both R&D scenarios (*Decarb_RD_GG* and *Decarb_RD_AG*) achieve cost reductions in green energy goods of up to 8.3% by 2050.



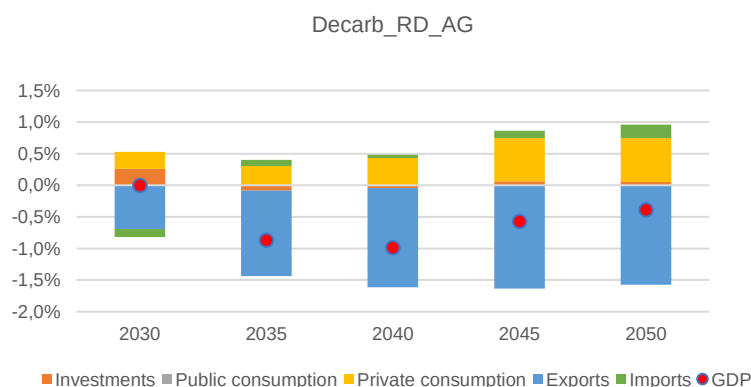
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As the cost of clean energy goods falls, households benefit from higher available income, which creates a ripple effect of increased consumption across the economy. This transition also provides a competitive edge for EU industries by lowering their energy-related production costs. With EU products becoming more competitive abroad, exports rise, and the combined pressure of domestic and foreign demand drives the investment needed to expand the region's productive capacity.

Figure 8: Decomposition of GDP changes by scenario - % change in GDP

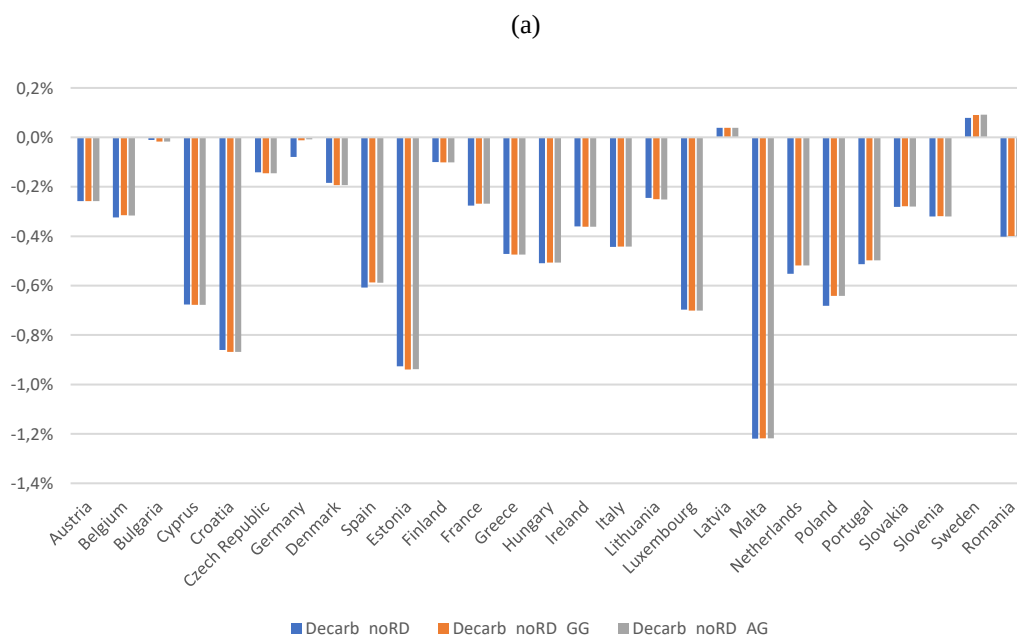




Source: GEM-E3

At the member state level, changes in the macroeconomic performance are most evident near the end projection period, when GDP impacts are found to be lower (on average) in the case of endogenous R&D compared to the noRD case. Countries with important industrial facilities such as Germany, Italy, France, Spain, Netherlands and Poland are found to have lower impacts compared to the case where noRD is included. However, at the Decarb_RD_AG case, where spillovers from other sectors are also included in the model gains are found to be lower as the relative additional productivity gains in most of the EU member states, with the exception of Germany are not so strong compared to the rest of the world.

Figure 9: GDP impacts at the Member State level - % change from Reference in 2030 (a) and 2050 (b)

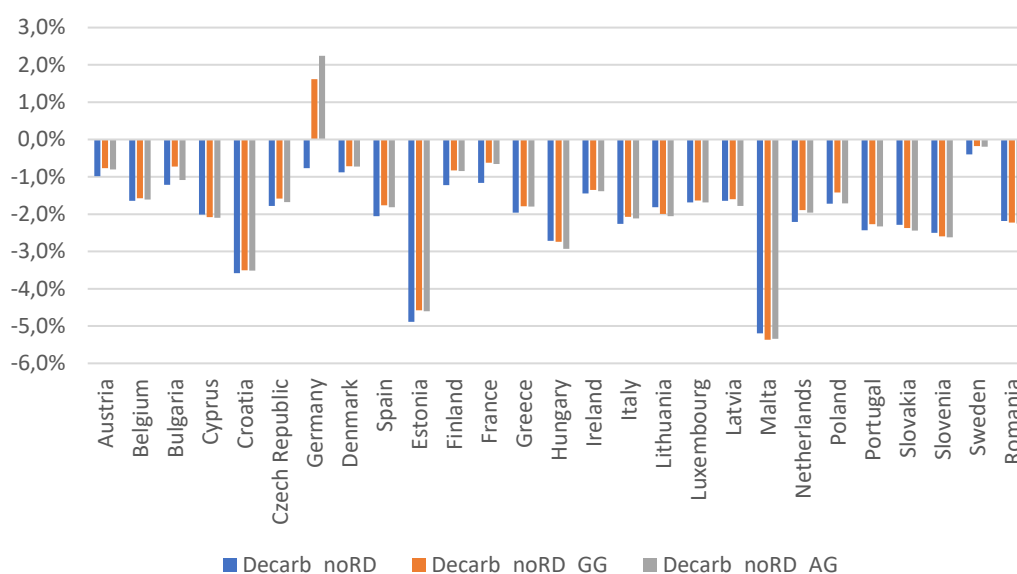


(b)



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Source: GEM-E3

2.3. Sectoral analysis

2.3.1. Production

Compared to the reference case, the decarbonization leads to lower overall sectoral production. Changes are driven mainly by manufacturing activities, as both energy-related costs and transitional shifts (towards RES) imply higher costs primarily for energy intensive industries. This generates a second order effect as it pushes higher the intermediate costs for all sectors using EU-based products, which adds up to the initial production cost changes.

However, the transition entails opportunities related to the production of clean energy goods and equipment. In our standard scenario (Decarb_noRd), production at the EU level is found to be higher by 1.6 times in 2030 and by 3.2 times in 2050 compared to the reference scenario. While accounting for R&D effects, those gains further expand especially in 2050 where production of those goods increases by 4.1 (Decarb_Rd_GG) to 4.3 (Decarb_RD_AG) times.

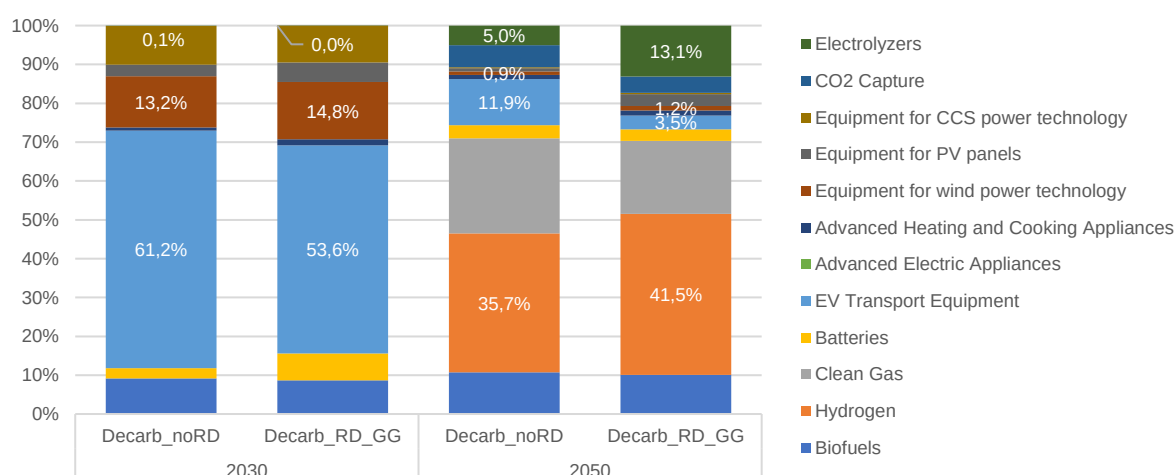
This increase is not linear. R&D innovation is projected to act in favor of hydrogen and electrolyzers to a higher extent and PV, while in 2030 it boosts the performance of activities related to the manufacturing of PV and wind equipment.

Figure 10: Sectoral production of green energy sectors – change from Reference



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Source: GEM-E3

Incorporating productivity improvements stemming from R&D expenditure implies gains for EU green sectors at the global level. The relatively high EU production of green goods on the road to achieve NETZERO lead to higher relative productivity gains compared to other countries, especially in the production of batteries and EV transport equipment where the respective share in the global market is found to be higher in both RD scenarios. The inclusion of spillover effects, however, does not act for the benefit of the EV manufacturing. As EU27 production in other key industries sectors is projected to fall intra-EU27 spillovers are expected to be lower compared to other countries, hindering the overall productivity improvements.

Figure 11: Changes in global production shares of green sectors for selected countries compared to the Decarb_noRD case in 2050– (a) Decarb_RD_GG (b) Decarb_RD_AG

(a)

	EU27	China	USA	Japan	Korea	India	RoW
Batteries	2.7%	-2.5%	0.4%	3.8%	0.0%	0.0%	-3.1%
EV Transport Equipment	1.2%	-0.4%	0.4%	0.0%	-0.7%	-0.1%	0.2%
Advanced Electric Appliances	-0.4%	1.8%	0.8%	-0.1%	0.0%	-0.3%	-0.7%
Heat pumps	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Equipment for wind power technology	0.4%	0.4%	0.9%	0.0%	-0.1%	-0.5%	-0.5%
Equipment for PV panels	-2.7%	1.3%	-0.4%	-0.1%	-0.4%	-1.4%	4.2%
Equipment for CCS power technology	20.0%	-1.5%	-0.6%	-2.3%	-0.4%	-0.6%	-7.7%
CO2 Capture	-5.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Electrolyzers	18.1%	8.1%	-11.0%	-2.8%	-3.7%	0.0%	-2.7%

(b)

	EU27	China	USA	Japan	Korea	India	RoW
Batteries	3.5%	-2.9%	0.2%	3.2%	-0.6%	0.0%	-2.2%
EV Transport Equipment	1.0%	-0.1%	0.7%	0.0%	-0.7%	-0.1%	-0.1%
Advanced Electric Appliances	-0.1%	0.3%	0.4%	0.0%	0.0%	-0.1%	-0.2%



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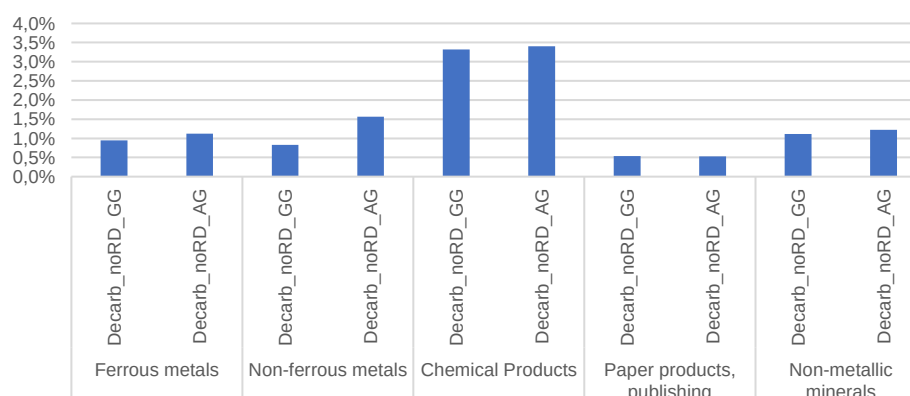


Heat pumps	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Equipment for wind power technology	0.9%	-0.8%	0.8%	0.0%	0.0%	-0.1%	-0.3%
Equipment for PV panels	-2.8%	1.4%	-0.4%	-0.1%	-0.4%	-1.4%	4.2%
Equipment for CCS power technology	20.6%	-1.5%	-1.2%	-2.3%	-0.4%	-0.6%	-7.7%
CO2 Capture	-5.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Electrolyzers	35.7%	-7.5%	-11.2%	-2.8%	-3.9%	0.0%	-2.8%

Source: GEM-E3

Disentangling the effects of the endogenous R&D mechanism on non-green energy sectors reveals a mixed landscape, with both winners and losers emerging. Compared to the noRD case, as the cost of green energy falls in the two RD scenarios, energy-intensive industries are expected to experience notable gains, benefiting from lower production costs and improved competitiveness (+1.7% to 1.8% in 2050). Market services and construction also expand, supported by rising private consumption and increased investment activity, particularly in infrastructure and green technologies. However, for many other sectors, higher economy-wide capital costs—driven by strong performance primarily in green and to a lesser extent in energy-intensive industries—limit their growth potential. Additionally, upward pressure on wages in market services contributes to a reallocation of resources.

Figure 12: EU27 – change in production of energy intensive sectors in 2050 compared to the Decarb_noRD case



Source: GEM-E3

2.3.2. International Trade

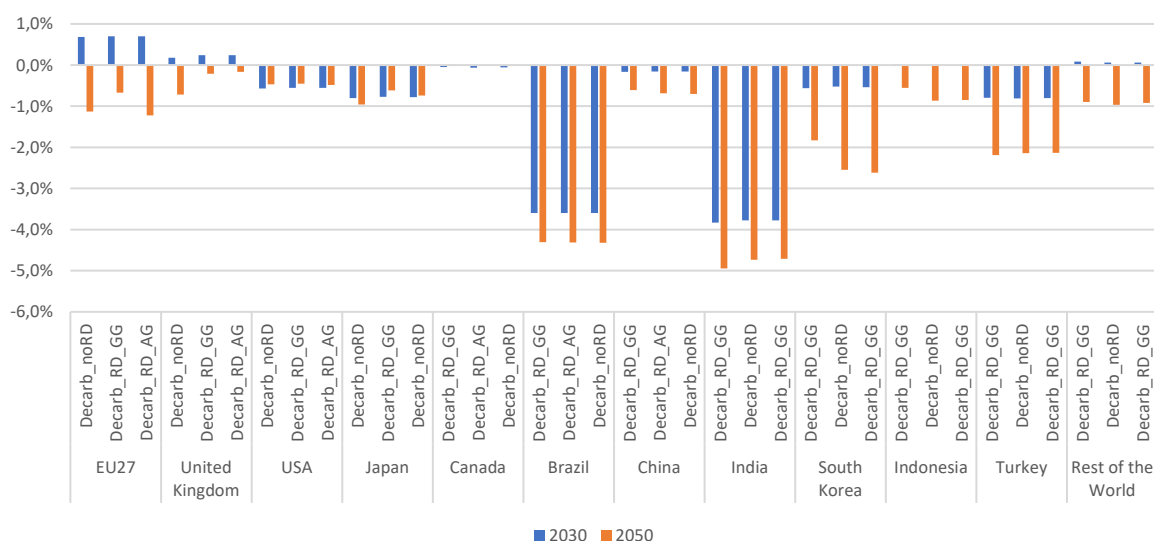
In terms of trade, the decarbonization yields negative effects for the EU27 trade surplus as i) the competitiveness of EU based goods and services falls due to higher costs and ii) large part of the equipment necessary for the transition is imported. On the other hand, China, USA and India record clear benefits as their imports fall and their exports increase. The introduction of the R&D mechanisms yields benefits in terms of trade balance for countries such as China, Japan and the ROW especially towards 2050 as their competitiveness increases. In the EU27, R&D induced productivity gains lead to lower export losses compared to the references scenario.



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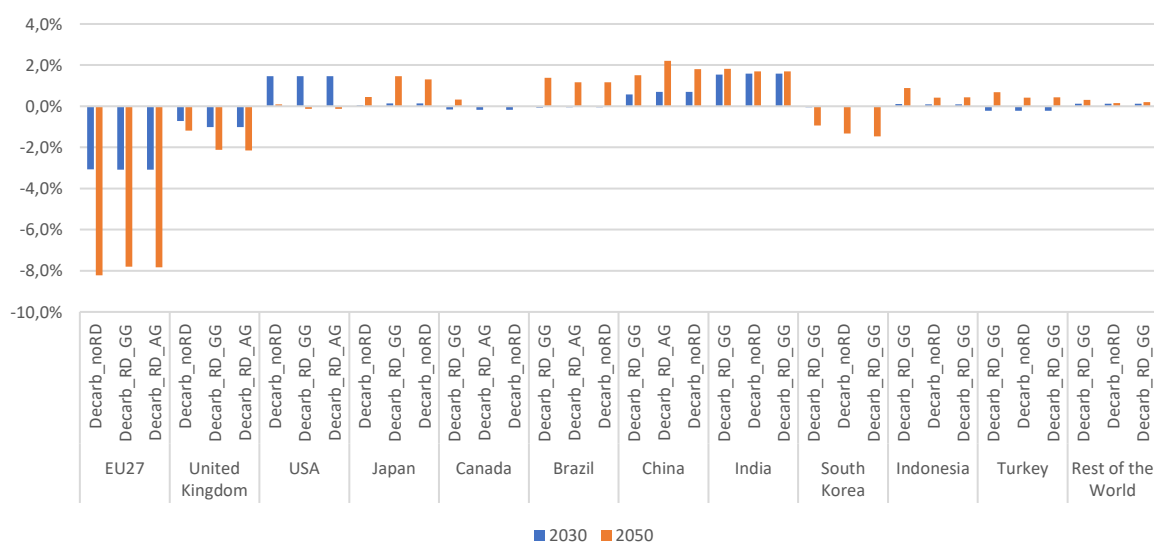


Figure 13: Imports (total) for selected countries - % change from Reference



Source: GEM-E3

Figure 14: Exports (total) for selected countries - % change from Reference



Source: GEM-E3

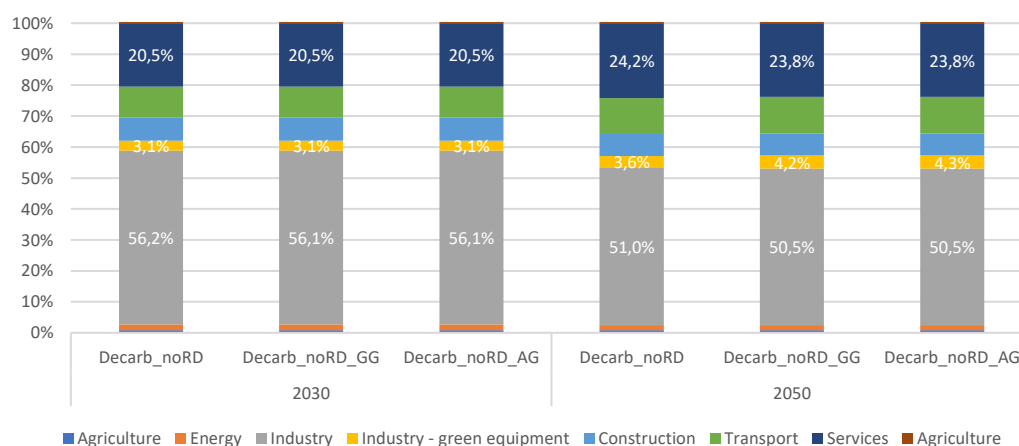
At the EU27 level, R&D-induced productivity in green sectors bolsters their competitiveness and increases their share of the region's export mix. Specifically, compared to the Decarb_noRD case, EU27 exports of green energy equipment rise by 18% and 19% in the Decarb_RD_GG and Decarb_RD_AG scenarios, respectively. While energy-intensive industries also benefit—with exports increasing by nearly 4% by 2050—these gains are offset by losses in other industrial sectors, resulting in a net negative effect for the aggregate sector.



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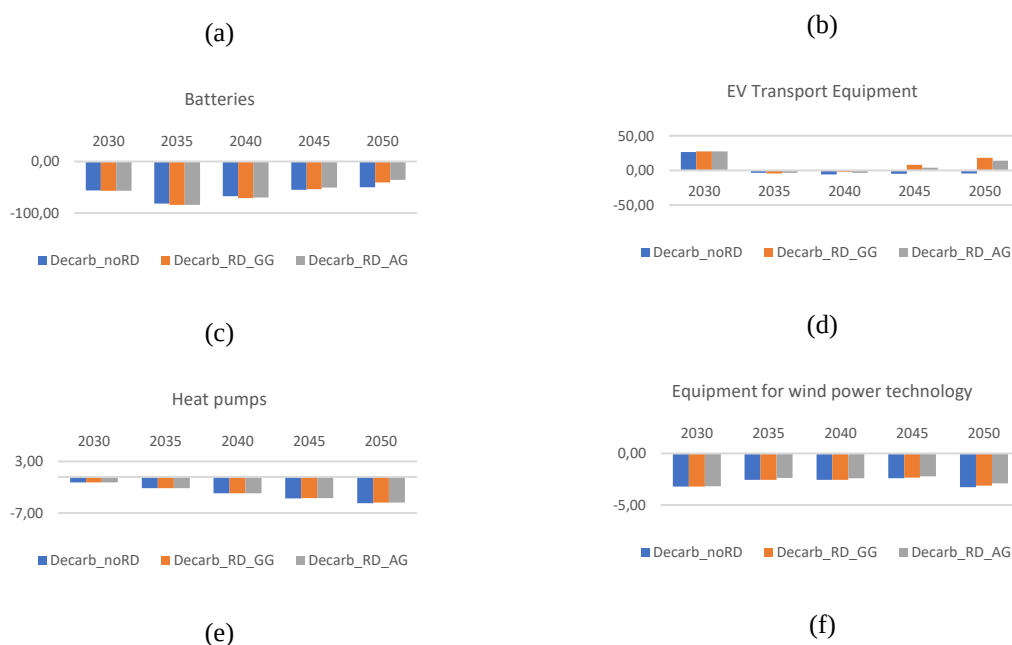
Figure 15: EU export composition in 2030 and 2050

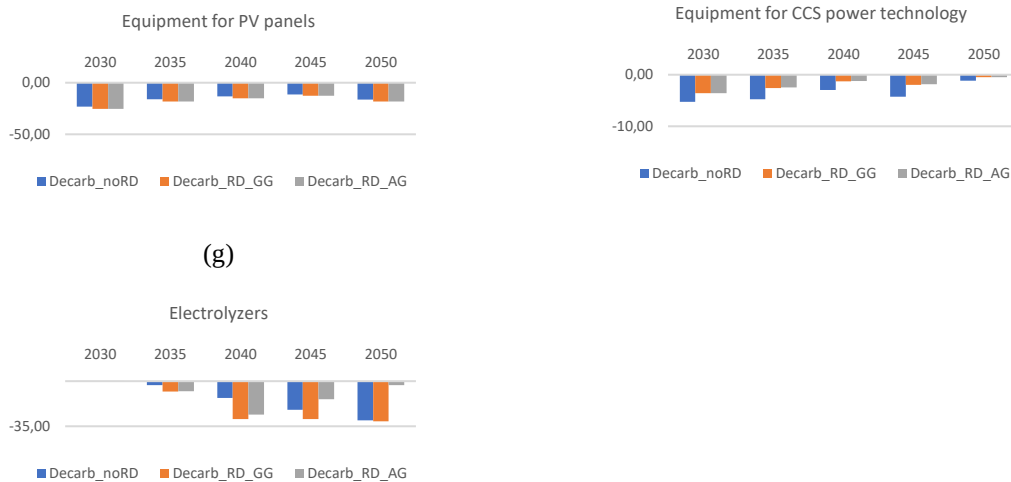


Source: GEM-E3

While domestic output is rising, the EU27 maintains a net importer status for clean energy equipment. The trade balance is forecasted to deteriorate until 2040, driven by the competitive advantage of Chinese manufacturers, before undergoing a long-term recovery by 2050. Specifically, the trade deficit contracts by 27% in the Decarb_RD_GG scenario and 54% in the Decarb_RD_AG scenario. Sectoral analysis indicates that R&D-induced productivity mitigates trade deficits in most green sectors, though electrolyzers remain an outlier to this trend.

Figure 16: Trade balance (green equipment sectors)





Source: GEM-E3

3. Quasi Monte Carlo

The objective of this section is to assess the model's sensitivity to uncertainty in the learning-by-research rate parameter. The analysis focuses on a single degree-of-freedom (1-DOF) problem, where the learning rate is treated as the sole uncertain input parameter. A representative technology from the electrolysis sector is selected for this sensitivity study, as electrolysis exhibits well documented learning-by-research behaviour and plays an increasingly important role in low carbon energy systems. This makes it a suitable benchmark for examining how uncertainty in learning rates propagates through the general computable equilibrium model.

A Quasi-Monte Carlo (QMC) approach based on Sobol low-discrepancy sequences is employed to efficiently sample the parameter space and evaluate the effect of the learning rate on key model outputs. Compared to standard Monte Carlo sampling, quasi-Monte Carlo methods typically demonstrate faster convergence, often approaching $\theta(N^{-1})$, relative to the $\theta(N^{-\frac{1}{2}})$ rate of conventional Monte Carlo methods, while providing more uniform coverage of the parameter domain.

3.1. Uncertain Parameter Definition

The uncertain input parameter is the learning-by-research rate, denoted by λ . Based on values reported in the literature for electrolysis technologies, the learning rate is assumed to lie within the interval:

$$\lambda \in [\lambda_{\min}, \lambda_{\max}]$$

Where,

$$\lambda_{\min} = 0.04, \lambda_{\max} = 0.199$$



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In the absence of prior information regarding the probability distribution of λ , a uniform distribution is assumed over this range:

$$\lambda \sim \mathcal{U}(\lambda_{\min}, \lambda_{\max}).$$

This assumption reflects epistemic uncertainty and ensures that all admissible learning-rate values are treated as equally likely.

3.2. Sobol Sequence Generation

Sampling is performed using a one-dimensional Sobol sequence, which generates a deterministic, low-discrepancy set of points in the unit interval:

$$u_i \in [0,1], \quad i = 1, \dots, N.$$

The Sobol sequence is generated with Owen scrambling enabled, which introduces controlled randomness while preserving the low-discrepancy properties of the sequence. Scrambling improves robustness and avoids potential alignment artefacts in low-dimensional problems. Each Sobol point is mapped from the unit interval to the physical parameter range using a linear transformation:

$$\lambda_i = \lambda_{\min} + (\lambda_{\max} - \lambda_{\min}) u_i.$$

The resulting samples $\{\lambda_i\}$ are then used as inputs to the GEM-E3 model.

3.3. Nested Sampling Strategy

A key property of Sobol sequences is their nested structure, whereby the first 2^p points of the sequence form a valid low-discrepancy set, and the first 2^{p-1} points are a subset of this set: $\{\lambda_1, \dots, \lambda_{2^{p-1}}\} \subset \{\lambda_1, \dots, \lambda_{2^p}\}$. This property is exploited to perform a systematic convergence analysis. The total number of simulations is increased sequentially as:

$$N = 2^p, \quad p = 4, 5, \dots, 11,$$

corresponding to sample sizes ranging from $N = 16$ to $N = 2048$. At each refinement level, only the newly added Sobol points are evaluated, while all previous model evaluations are retained. This ensures computational efficiency and full reproducibility of results.

3.4. Model Evaluation and Output Statistics

For each learning-rate sample λ_i , the GCE model is executed, and a set of key output quantities is recorded. Let $Y(\lambda)$ denote a generic model output of interest. For a given sample size N

, the QMC estimator of the mean output is computed as:

$$\bar{Y}_N = \frac{1}{N} \sum_{i=1}^N Y(\lambda_i).$$



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The corresponding sample standard deviation is given by:

$$\sigma_N = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (Y(\lambda_i) - \bar{Y}_N)^2}.$$

These statistics are evaluated for each key output variable at every sampling level $N = 2^p$.

3.5. Convergence Assessment

Convergence of the QMC simulations is assessed by monitoring the stability of the mean of selected key outputs as the number of samples is doubled.

3.6. Mean Convergence Criterion

For two successive sample sizes $N = 2^{p-1}$ and $2N = 2^p$, the relative change in the estimated mean is computed as:

$$\Delta_{\text{mean}}^{(p)} = \frac{|\bar{Y}_{2^p} - \bar{Y}_{2^{p-1}}|}{|\bar{Y}_{2^{p-1}}|}.$$

Convergence with respect to the mean is assumed when:

$$\Delta_{\text{mean}}^{(p)} < 5\%.$$

3.7. Interpretation

The nested Sobol framework allows convergence to be assessed without discarding previous simulations, ensuring that changes in output statistics are solely attributable to increased sampling resolution rather than stochastic noise. When both the mean and standard deviation criteria are satisfied for all key outputs, the QMC sample size is considered sufficient. Here, the following GEM-E3 key outputs are considered for the convergence assessment: GDP, electrolyzers production, exports, and imports. The values for these outputs are taken for Germany which represents a major industrial producer in the EU.

3.8. Results

Table 4 summarizes the convergence results obtained from the Quasi Monte Carlo runs with 16 and 32 simulations. The key mean GEM-E3 output metrics are reported for Germany along with the % difference as the number of simulations are doubled from 16 to 32. As can be seen, as the number of simulations is doubled, the mean for all four parameters of interest remains well below the very conservative threshold of 1% with exports and Electrolyzer production showing the largest change at ~0.55% and ~0.43% respectively. Hence, it can be concluded that the Quasi Monte Carlo simulations have converged.



Table 4: Convergence results showing the core mean values of interest for the country of Germany (GDP, electrolyzers production, exports, and imports) obtained with increasing number of Quasi Monte Carlo simulations N and their difference.

	$N = 16$	$N = 32$	Difference
GDP	5602.534794	5602.199432	0.006 %
Electrolyzer production	18.045565	17.968946	0.425 %
Exports	5.847913	5.815680	0.551 %
Imports	6.548822	6.545925	0.044 %

Source: author's calculations

Following the convergence assessment, we explore how the core macroeconomic and sectoral outputs of the GEM-E3 model respond to variations in the learning-by-research learning rate. Figure 17 reveals that GDP exhibits a clear and predominantly monotonic increasing trend as the learning rate rises. Apart from a single low-value outlier near the lower edge of the sampled range, the trajectory is smooth and tightly clustered. This behavior is consistent with the expectation that stronger technological learning reduces costs and enhances overall productivity, which in turn translates into higher macroeconomic output. Electrolyzer production (Figure 18) displays a similarly monotonic response: production rises steadily with the learning rate, and the slope increases slightly toward the upper end of the range. This indicates that technology cost reductions associated with learning-by-research have a strong and accelerating impact on hydrogen-related industrial output.

The trade variables (imports and exports shown in Figure 19) show a more nuanced pattern. Exports rise consistently over nearly the entire range, with only minor irregularities at the lowest learning rates. This suggests that cost-improving technological learning enhances the competitiveness of domestic production, enabling greater export penetration. Imports do not exhibit strict monotonicity. Instead, they show a relatively flat region at moderate learning rates, followed by mild decreases and even a small uptick at the high end of the range which correlates with a sudden drop in exports. While the overall variation remains small compared to the absolute level, the shape of the curve hints at the presence of structural threshold effects or nonlinear adjustments within the production–trade system. The combination of monotonicity in GDP and production with localized nonlinearities in trade flows highlights that the learning-by-research mechanism influences the system through both smooth productivity channels and more complex general-equilibrium adjustments.

Figure 17: GDP in millions vs learning by research learning rate for Germany.



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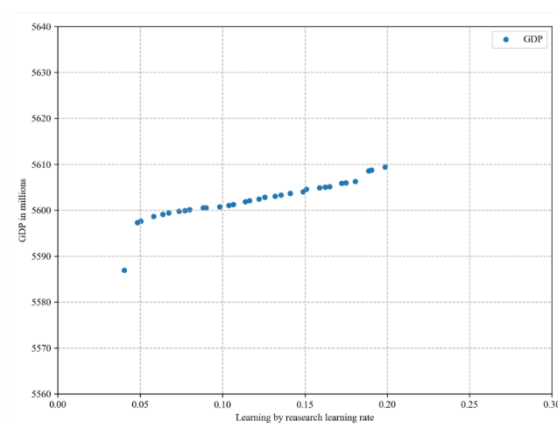


Figure 18: electrolyzer production in Germany vs learning by research learning rate for Germany.

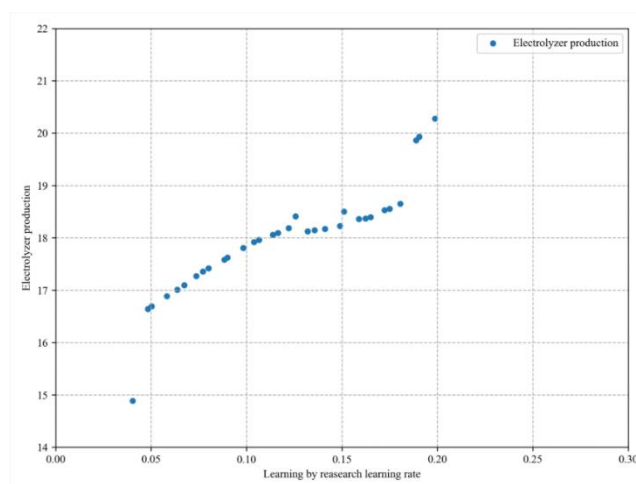
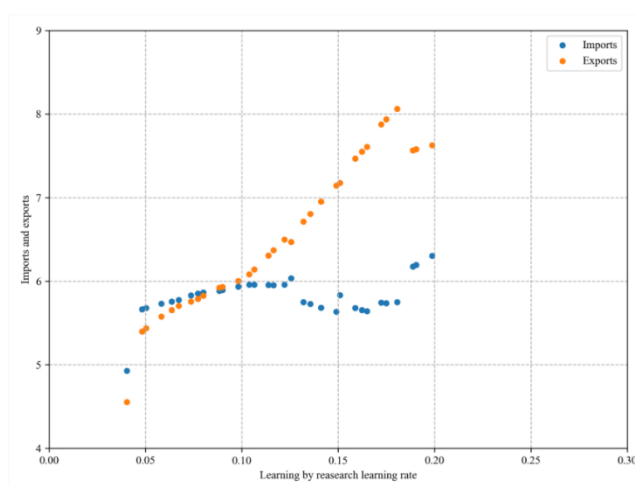


Figure 19: Imports and exports of electrolyzers in Germany



4. Conclusions and next steps

The extension of the model to endogenously account for R&D-driven productivity gains significantly enhances the robustness and realism of the assessment. First, the model is now better equipped to capture the dynamic cost reductions that accompany the introduction and diffusion of new technologies within the energy mix. These cost shifts influence not only the adoption rate of green technologies but also generate indirect effects across all other sectors of the economy. In addition, the model more accurately reflects the trade-related mechanisms that determine which countries stand to benefit most during a green transition, particularly through changes in comparative advantage and technology-embedded exports. Finally, incorporating a detailed and empirically grounded spillover matrix is crucial for correctly estimating patterns of knowledge diffusion, ensuring that innovation benefits are allocated in a realistic and sector-specific manner.

However, several challenges and potential pitfalls require careful attention. Data limitations related to the measurement of R&D stocks and the assumed learning rates can substantially affect the model's outcomes. For learning rates in particular, the literature offers a wide range of estimates across technologies, making sensitivity analysis essential to ensure the robustness of results. Moreover, general equilibrium models tend to be highly sensitive to changes in relative prices, meaning that calibration must be handled with particular care. Parameter choices should be consistent with the model's structural features, and adjustments may be necessary to avoid distortions or unrealistic sectoral responses.

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6. Annex

6.1.1. GEM-E3 model dimensions

Table 5: Regional resolution of the GEM-E3 model

Code	Country/region	Code	Country/region
AUT	Austria	USA	USA
BEL	Belgium	JPN	Japan
BGR	Bulgaria	CAN	Canada
CYP	Cyprus	BRA	Brazil
CRO	Croatia	CHN	China
CZE	Czech Republic	IND	India
DEU	Germany	KOR	South Korea
DNK	Denmark	IDN	Indonesia
ESP	Spain	MEX	Mexico
EST	Estonia	ARG	Argentina
FIN	Finland	TUR	Turkey
FRA	France	SAR	Saudi Arabia
GBR	United Kingdom	OCE	Oceania
GRC	Greece	RUS	Russian federation
HUN	Hungary	ARE	United Arab Emirates
IRL	Ireland	REP	Rest of energy producing countries
ITA	Italy	SAF	South Africa
LTU	Lithuania	REU	Rest of Europe
LUX	Luxembourg	ROW	Rest of the World
LVA	Latvia		
MLT	Malta		
NLD	Netherlands		
POL	Poland		
PRT	Portugal		
SVK	Slovakia		
SVN	Slovenia		
SWE	Sweden		
ROU	Romania		

Table 6: Sectoral resolution in GEM-E3



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Code	Sector	Code	Sector
AGR01	Agriculture	IND17	Heat pumps
ENE01	Coal	IND18	Equipment for wind power technology
ENE02	Crude Oil	IND19	Equipment for PV panels
ENE03	Oil	IND20	Equipment for CCS power technology
ENE04	Gas	IND21	CO2 Capture
ENE05	Power Supply	IND22	Electrolyzers
ENE06	Biomass Solid	TRA01	Warehousing
ENE07	Biofuels	TRA02	Air transport
ENE08	Hydrogen	TRA03	Land transport
ENE09	Clean Gas	TRA04	Water transport
IND01	Ferrous metals	SRV01	Market Services
IND02	Non-ferrous metals	SRV02	Non Market Services
IND03	Fabricated Metal products	SRV03	R&D
IND04	Chemical Products	PGT01	Coal fired
IND05	Basic pharmaceutical products	PGT02	Oil fired
IND06	Rubber and plastic products	PGT03	Gas fired
IND07	Paper products, publishing	PGT04	Nuclear
IND08	Non-metallic minerals	PGT05	Biomass
IND09	Computer, electronic and optical products	PGT06	Hydro electric
IND10	Transport equipment (excluding EV)	PGT07	Wind
IND11	Other Equipment Goods	PGT08	PV
IND12	Consumer Goods Industries	PGT09	Geothermal
IND13	Construction	PGT10	CCS coal
IND14	Batteries	PGT11	CCS Gas
IND15	EV Transport Equipment	PGT12	CCS Bio
IND16	Advanced Electric Appliances		

6.1.2. Innovation diffusion matrix

The subsequent paragraphs provide a detailed overview of the innovation diffusion table creation as performed by the publicly available ADD_NAME_HERE.R script. The script uses three main categories of input datasets:

- 1) **Patent Citation Data:** Located in the Raw_Data/ folder, the Fractional_Citations_6_yearlyCohorts_Of_CitedFam.csv file contains fractional forward citations between patent families and includes citing and cited countries, NACE2 technology classes, and weighted citation counts.
- 2) **Patent Family Counts:** Located in the Raw_Data/ folder, the AllTech_Fractional_FamilyCounts.xlsx file provides fractional counts of patent families



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per inventor country and NACE2 sector classification. This file is used to compute patent intensities and to normalize patent citation flows.

- 3) **Mapping Tables:** Mapping tables are used to map inventor countries to GEM-E3 regions (Cited_reg_geme3.csv, Citing_reg_geme3.csv files located in the Mapping_Regions/folder) and NACE2 technology codes to GEM-E3 economic sector (nace2_green_geme3.xlsx located in the Mapping_Sectors/ folder).

The ADD_NAME_HERE.R script takes the input data and performs the following data cleaning and data manipulation actions before producing the final innovation diffusion table:

- 1) **Aggregation of raw patent citation flows:** Patent citations are aggregated by cited country & NACE2 code and by citing country & NACE2 code. All missing and non-applicable values are removed. All entries are filtered and only those with the green energy technology designation are kept {Perhaps we should justify this}.
- 2) **Patent citation flows regional aggregation:** Countries are mapped to GEME3 regions (both cited and citing sides) and patent citation flows are reaggregated at the GEME3 regional level. Table 2 shows the Country to GEM-E3 country code mapping. A one to one mapping is employed between the database and GEM-E3 countries with any database country that does not appear in Table 2 being incorporated into the rest of the world (ROW) region.
- 3) **Patent citation flows sectoral aggregation:** NACE2 technology fields are mapped to GEME3 sectors (see Table 1 for the full mapping). Patent citation flows are reaggregated at the GEME3 sectoral level. The resulting dataset is a complete table containing both the citing and cited region and sector.
- 4) **Patent family aggregation:** Patent families are aggregated similarly first by country and NACE2 and then mapped to GEME3 regions and sectors following the aforementioned mappings. This yields the total fractional patent families per region–sector.
- 5) **Calculation of patent intensities:** For each region–sector pair we calculate the patent intensity by dividing the fractional patent families by the total incoming patent citations, reflecting how research activity translates into patented innovations.
- 6) **Conversion of citation flows into patent-weighted flows:** Using the patent-intensity metric derived in the previous step, the citation flow matrix is transformed into a patent-weighted flow matrix. Patent intensity links the total number of patent families in each region–sector to the total number of incoming patent citations, allowing us to approximate the volume of patented technological knowledge embodied in each citation flow. By multiplying each citation flow by the patent intensity of the



corresponding citing region–sector, citation counts are converted into “patent-weighted” flows that reflect how many patented innovations are effectively transmitted across regions and sectors. This step is essential, as it allows the diffusion of patented knowledge to be expressed in units comparable to the patent family counts used elsewhere in the methodology.

- 7) **Construction of the innovation diffusion table:** Patent citation flows and patent intensities are combined to estimate the patented knowledge embodied in incoming patent citations, and the distribution of these patents across citing sectors/regions. The innovation diffusion coefficient expresses how strongly region–sector A benefits from research produced in region–sector B.
- 8) **Final filtering:** All entries with missing mappings (regions, sectors, or values) are excluded.
- 9) **Final output:** The script produces a clean, deduplicated innovation diffusion table `Spillovers_GEME3_AA.xlsx` containing: Cited GEME3 region, Cited GEME3 sector, Citing GEME3 region, Citing GEME3 sector, and the estimated innovation diffusion coefficient. This table is then imported into the GEME3 model, enabling macroeconomic simulations that incorporate empirical, data-driven cross-sector and cross-regional technology innovation diffusion.



