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Summary

This paper evaluates the macroeconomic and financial risks of the energy transition using an extended MATRIX model, a multi-agent, multi-sector integrated assessment framework for the Euro Area. The model features endogenous, directed technical change in the energy sector and a decentralized electricity market based on merit-order rule. Energy firms switch technologies based on relative profitability, capturing feedback loops between R&D, productivity gains, and competitiveness, which may lead to either brown lock-in or green energy transition. We compare conventional policies – brown tax (BT), unconditional green subsidy (GS), and conditional green subsidy (CGS) linked to R&D – with alternative policy mixes, such as coordinated monetary policy, green finance and green industrial policy. Results show that while conventional policies modestly increase transition likelihood, they entail GDP losses due to production and financial constraints. These can be mitigated with green industrial policy and green finance, which alleviate sectoral bottlenecks and foster a more effective transition.

Keywords: Energy Sector, Agent-Based Models, Macroeconomic Dynamics, Directed Technological Change, Green Transition

JEL classification: C63, E61, O33, Q43, Q55

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Taking the green pill: Macro-financial transition risks and policy challenges in the MATRIX model

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Abstract

This paper evaluates the macroeconomic and financial risks of the energy transition using an extended MATRIX model, a multi-agent, multi-sector integrated assessment framework for the Euro Area. The model features endogenous, directed technical change in the energy sector and a decentralized electricity market based on merit-order rule. Energy firms switch technologies based on relative profitability, capturing feedback loops between R&D, productivity gains, and competitiveness, which may lead to either brown lock-in or green energy transition. We compare conventional policies – brown tax (BT), unconditional green subsidy (GS), and conditional green subsidy (CGS) linked to R&D – with alternative policy mixes, such as coordinated monetary policy, green finance and green industrial policy. Results show that while conventional policies modestly increase transition likelihood, they entail GDP losses due to production and financial constraints. These can be mitigated with green industrial policy and green finance, which alleviate sectoral bottlenecks and foster a more effective transition.

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1. Introduction

The imperative to address climate change has brought the orderly energy transition to the forefront of global policy discussions. This transition requires the widespread development and diffusion of clean technologies, i.e., innovative production methods that reduce environmental impact. However, market mechanisms alone have proven insufficient in driving the necessary investments in these technologies, primarily due to persistent market failures (Popp, 2019). Consequently, well-designed policy interventions are essential to redirect innovation from environmentally detrimental practices toward more sustainable alternatives.

Nevertheless, achieving a smooth and orderly transition remains a complex challenge. Despite increasing policy effort, the current trajectory falls short of the ambitious targets outlined in the International Energy Agency's Net Zero Emissions scenario (IEA, 2021). The pace of low-carbon innovations, measured by the share of green patents, has decelerated over the past decade and is insufficient to meet carbon neutrality goals (Cervantes et al., 2023).

In this context, the effectiveness of conventional climate policies, such as carbon tax and green subsidies, in securing a smooth transition is not guaranteed (Campiglio, 2016). Traditional policies face several challenges that may hinder or delay an orderly transition, including technological lock-in, bottlenecks in supply chains for critical resources, potential imbalances in energy markets, insufficient funding for crucial investments and weak political support. Cervantes et al. (2023) contend that green industrial and innovation policies targeting low-carbon technologies are essential complements or alternatives to carbon pricing, addressing market failures and barriers to innovation that conventional policies struggle to overcome. Additionally, poorly designed policies may introduce macro-financial transition risks, such as default risk due to increased production costs from carbon taxes or market distortions resulting from green subsidies, potentially undermining transition objectives (Semieniuk et al., 2021). To improve the likelihood of a smooth transition and minimize associated costs, macroeconomic policies must create favorable conditions for green investment, underscoring the need for coordinated environmental, fiscal, and monetary policies to support the transition effectively (Schmidt et al., 2019).

In light of this, several critical questions arise: What are the most effective policies for facilitating a rapid and orderly energy transition? What macro-financial risks are associated with it? How can transition policies be designed to mitigate these risks? And what role should fiscal and monetary policy play in supporting the transition? Addressing these questions requires a modeling framework that can capture potential coordination failures, real-financial linkages, and out-of-equilibrium dynamics that may emerge throughout the transition pathway.

Several studies have examined the macroeconomics of the green transition within a general equilibrium framework, including endogenous growth models (Acemoglu et al., 2012, 2016), integrated assessment models (Bosetti et al., 2009; Emmerling et al., 2016), and computable general equilibrium models (Burniaux and Truong, 2002; Bosello et al., 2012). More recently, the macroeconomic effects of carbon pricing have been analyzed using the European Central Bank's New Area-Wide Model, a nonlinear two-country DSGE model augmented with a decentralized energy sector (Coenen et al., 2024).

While these models provide valuable insights, they often downplay critical perturbing factors such as bounded rationality, uncertainty, incomplete information, as well as the complexities of production and financial networks. These factors represent endogenous sources of macro-financial risks associated with the energy transition. Consequently, these models may underestimate the challenges and risks associated with the low-carbon transition (Farmer et al., 2015; Balint et al., 2017).

Agent-based integrated assessment models (ABMs), by incorporating agent heterogeneity, bounded rationality, and decentralized market interactions, have gained increasing recognition for analyzing the complex interactions between the economy and the environment (Balint et al., 2017). Compared to traditional IAMs, AB-IAMs offer a more robust framework for capturing the uncertainty, non-linearities, and risks inherent in the transition to a low-carbon economy (Hansen et al., 2019; Castro et al., 2020).

In this paper, we use the MATRIX model (*Multi-Agent model for Transition Risks*) to assess the impacts of environmental policies on the likelihood of energy transition and the associated macro-financial risks. MATRIX is an agent-based integrated-assessment model for the Euro Area, featuring a multi-agent, multi-sector macroeconomic module coupled with a flexible climate module that incorporates a carbon cycle and a carbon damage function. The model has been previously applied to investigate the economic and distributional impacts of energy shocks (Ciola et al., 2023), macro-stabilization policies in response to energy price shocks, (Turco et al., 2023), the effects of climate change and mitigation policies (Bazzana et al., 2024), and the role of green preferences versus supply-side policies in driving low-carbon transition (Rizzati et al., 2024).

To address the goals of this paper, we implement three major enhancements to the MATRIX framework. First, we expand the energy sector by introducing a diversified energy mix that includes *clean* and *dirty* plants, each with specific features regarding duration, input requirements and cost structure, calibrated to reflect an initial cost gap in 2000 based on IEA (2005) data. Second, we introduce an *endogenous* growth process in two different forms: (i) *learning by doing* in all industrial sectors, which is based on workers' skills accumulation depending on past employment status; (ii) *R&D investment* in the energy sector, based on energy plants' past profitability. Third, we model a *real-world electricity market* incorporating differentiated time periods (peak and off-peak hours) and merit order rule, where heterogeneous energy firms submit price-quantity bids sorted by price to construct the energy supply curve and the market price is determined by the system marginal price, i.e. the price of the marginal power plant required to meet total demand.

We analyze the energy transition by allowing energy firms to switch technologies based on their relative profitability, following the directed technical change tradition (Acemoglu et al., 2012). Specifically, once a plant reaches its maximum lifecycle, a firm can choose to either re-invest in the same type of plant or switch to a different technology, depending on the relative average profitability of clean versus dirty technologies. This framework captures potential feedback loop between R&D investment, productivity gains, enhanced competitiveness, higher infra-marginal profits via merit order rule, and subsequent R&D investment. Consequently, two possible trajectories may arise in the energy sector: brown technological lock-in, where dirty firms consolidate their competitive advantage due to path dependence, or green energy transition, where clean plants become more competitive through effective R&D investment.

We use the extended MATRIX model to evaluate the impacts of various environmental policies on the likelihood of energy transition and associated macro-financial costs. The policies considered include: (i) a brown tax (BT), levied on the profits of firms operating dirty plants; (ii) an unconditional green subsidy (GS), financed by BT revenues and distributed to firms adopting clean plants; and (iii) a conditional green subsidy (CGS), similarly funded by BT revenues, but allocated to clean firms contingent on their R&D investment. In addition, we compare these conventional policy approaches with alternative policy mixes, including coordinated monetary policy, green financing, and green industrial policy.

This paper contributes to the growing literature on the macroeconomic impacts of the energy transition through the use of agent-based models (ABMs). Using the DSK model, Lamperti et al. (2020) show that in the absence of climate policies the economy exhibits non-ergodic beaviour, resulting in two potential equilibria: carbon lock-in or green transition, with the former being more likely but less economically efficient. Moreover, they find that climate shocks, particularly energy efficiency shocks, significantly impact transition probabilities, while traditional carbon taxes are largely ineffective. Ponta et al. (2018), using the EUGE model (Eurace@Genoa), demonstrate that feed-in tariffs can drive green investment in energy sector but lead to adverse economic effects at higher intensities. Nieddu et al. (2024) extend this analysis by comparing feed-in tariffs and carbon taxes, finding the former more effective but with diminishing benefits at higher intensities. Hötte (2020) employs the EUBI model (Eurace@Bielefeld) to investigate the role of knowledge accumulation on path dependence and green technology diffusion, showing that policy effectiveness depends on overcoming technological barriers, with taxes outperforming subsidies when productivity gaps persist. Safarzyńska and Van Den Bergh (2022) underline the critical link between optimal climate policy and income inequality, demonstrating that lower labor income inequality correlates with an increased social cost of carbon (SCC), whereas the impact of capital income inequalities on the SCC varies based on the proportion of the population receiving capital rents. Albeit not fully agent-based, Dafermos et al. (2018) develop an aggregate dis-equilibrium stock-flow consistent model to examine the impacts of climate change on financial stability, showing that a green monetary policy can significantly mitigate climate-related financial risks. Similarly, Monasterolo and Raberto (2018) demonstrate how green fiscal and monetary policies can foster green growth by influencing firm expectations and credit markets.

While our agent-based integrated assessment framework shares similarities with the work of Lamperti et al. (2020), Ponta et al. (2018) and, to some extent, Hötte (2020), our paper advances the literature on the macroeconomic impacts of the energy transition by addressing limitations in existing models and introducing novel policy experiments. Both the DSK model (Lamperti et al., 2020) and the EUGE model (Ponta et al., 2018; Nieddu et al., 2024) present a centralized representation of the energy sector, with one or two producers reliant on either brown or green plants, consistently capable of meeting energy demand. In contrast, our MATRIX model proposes a decentralized energy sector composed of heterogeneous energy firms competing in a realistic electricity market governed by merit order rule. This decentralized framework better captures the market frictions that may arise during the energy transition, offering valuable insights into the challenges regulators may face when managing the electricity grid. Indeed, although the energy sector is subject to significant regulation, our approach allows for a more detailed examination of potential sources of financial risks and market imbalances that may emerge throughout the transformation process.

Moreover, our model enhances the representation of green and brown technologies by directly calibrating key characteristics - such as initial share of green firms, plant duration, factor shares, and cost structures - using empirical data for the Euro Area. This calibration provides a more accurate depiction of the technological dynamics driving the energy transition.

Furthermore, our paper implements a comprehensive set of policy experiments, extending beyond the focus of previous models that often examine specific climate policies, such as carbon taxes or feed-in tariffs. We explore a broader spectrum of interventions, specifically assessing the interaction between climate policies and monetary, fiscal, and industrial policies, in line with the work of Dafermos et al. (2018) and Monasterolo and Raberto (2018). This approach offers a more holistic view of how different policy mixes influence the transition towards a low-carbon economy. A similar approach is taken by Lamperti et al. (2024), who compare command-and-control regulatory measures (e.g. ban on fossil fuel use) with conventional transition policies, such as carbon taxes and green subsidies.

Overall, the extended MATRIX model enables a deeper analysis of the complexities and policy trade-offs inherent in the energy transition, providing valuable insights for policymakers and regulators seeking to manage the macroeconomic and financial risks associated with climate change.

In Section 2, we detail the extensions proposed for the MATRIX model. Section 3 describes the calibration and the proposed policy experiments. In Section 4, we present the simulation results and discuss them. Section 5 provides concluding remarks.

2. Methodology

The MATRIX model (Bazzana et al., 2024) is an agent-based integrated assessment model that combines an economic and a climate module. The economic module features a multi-sector, multi-agent macroeconomic framework calibrated for either the Euro Area (EA) or the United States (US). Heterogeneous agents - households, firms, banks, and public entities - interact within decentralized markets under conditions of incomplete information. While agents aim to follow optimal behavioral rules, they adjust their control variables through adaptive learning. Market interactions take place via search and matching mechanisms, capturing real-world frictions (Delli Gatti et al., 2011, 2018; Yashiv, 2007). Industrial sectors are linked through empirically calibrated input-output relationships and include intermediate capital goods (K), a final consumption goods (C), energy services (E), and exogenous fossil fuel inputs (F). The flowchart of the model is presented in Figure 1. The climate box within the MATRIX model is a flexible module that incorporates a range of carbon cycle and climate damage functions drawn from the scientific literature. However, as this paper does not focus on climate dynamics, we deactivate this module for the analysis presented here.

To address our research questions, we extend the MATRIX model along three main dimensions. Before discussing these extensions, we outline the equations governing firms behavior.[1]

Firms behavior. Firms, categorized into three sectors (E, C, K), determine their desired price and quantity using an adaptive learning mechanism based on market conditions and strategic interaction (Assenza et al., 2015; Poledna et al., 2023). Specifically, they set their $\{P, Q\}$ combination by either imitating a more profitable target competitor[2] or exploring a neighboring strategy.

Firm f updates its desired quantity and price $\{Q_{f,t+1}, P_{f,t+1}\}$ as follows:

$$Q_{f,t+1} = \begin{cases} \zeta^Q Q^*_{f,t} + (1-\zeta^Q) Q_{s,t} & \text{if } \Pi_{s,t} \geq \Pi_{f,t}, \\ \zeta^Q Q^*_{f,t} + (1-\zeta^Q) \hat{Q}_{f,t} & \text{otherwise,} \end{cases} \tag{1}$$

[1]For a detailed description of the model, see Ciola et al. (2023) and Bazzana et al. (2024). A brief overview of the other main sectors is provided in Appendix A.

[2]The target competitor is chosen through a logit model computed as the difference between firms' relative production: $d_{f,s,t} = |\hat{y}_{f,t} - \hat{y}_{s,t}|$, where $\hat{y}_{f,t} \equiv \frac{P_{f,t}Q_{f,t} - \min(P_{f,t}Q_{f,t})}{\max(P_{f,t}Q_{f,t}) - \min(P_{f,t}Q_{f,t})}$.

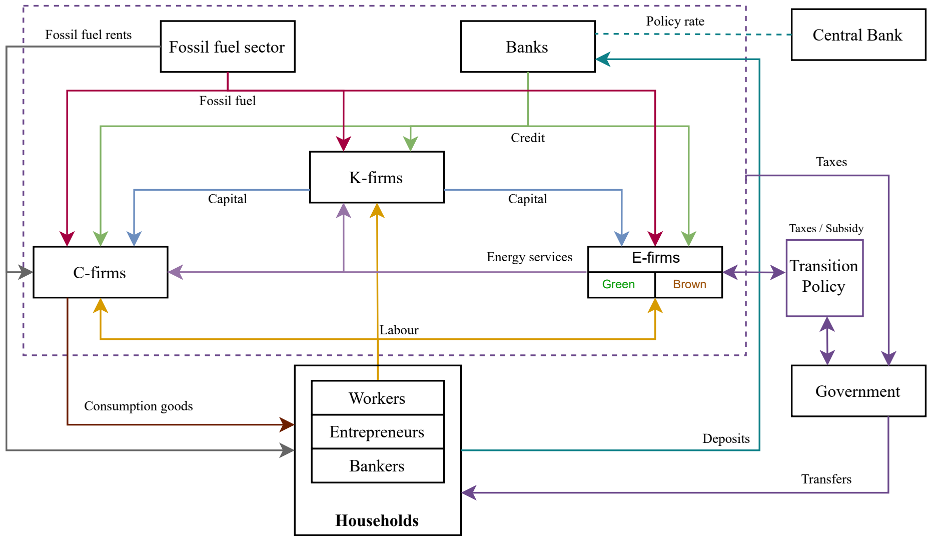

Figure 1: Flowchart of the MATRIX model

$$P_{f,t+1} = \begin{cases} \zeta^P P_{f,t} + (1-\zeta^P) P_{s,t} & \text{if } \Pi_{s,t} \geq \Pi_{f,t}, \\ \zeta^P P_{f,t} + (1-\zeta^P) \hat{P}_{f,t} & \text{otherwise,} \end{cases} \tag{2}$$

where $P_{s,t}$, $Q_{s,t}$, and $\Pi_{s,t}$ are the price, quantity, and profits of the target competitor s, while ζ^Q and ζ^P indicate the adjustment speed of price and desired quantity. If s's profits exceed f's, the latter adjusts towards them. Otherwise, f explores a neighborhood of its current strategy, $\hat{Q}_{f,t}, \hat{P}_{f,t}$, by drawing a random number from a uniform distribution, positive for excess demand and negative for excess supply.

Given $Q^*_{f,t+1}$ (desired production) and $\{\mathbb{E}_{f,t}\left[P_{j,t+1}\right]\}_{j=1}^n$ (expected input prices), each firm f sets the conditional input demand to minimize its expected direct costs $\mathbb{E}_{f,t}\left[DC_{f,t+1}\right]$. Given the Constant Elasticity of Substitution (CES) production technology with irreversible investments, the cost minimization problem reads:

$$\min_{\{X_{f,j,t+1};\Delta X_{f,j,t+1}\}_{j=1}^{J}} \mathbb{E}_{f,t}\left[DC_{f,t+1}\right] = \sum_{j=1}^{n} \mathbb{E}_{f,t}\left[P_{j,t+1}\right] \Delta X_{j,f,t+1} \tag{3}$$

$$\text{s.t.} \quad Q^*_{f,t+1} = \left[\sum_{j=1}^{J} A_{j,f,t+1}\left(X_{j,f,t+1}\right)^{\rho_f}\right]^{\frac{1}{\rho_f}}, \tag{4}$$

$$X_{j,f,t+1} = \Delta X_{j,f,t+1} + (1-\delta_j)X_{j,f,t}, \tag{5}$$

$$\Delta X_{j,f,t+1} \geq 0 \text{ when } j \text{ indicates physical capital}, \tag{6}$$

where $\Delta X_{j,f,t+1}$, δ_j, and $A_{j,f,t+1}$ are the additional input demand, depreciation rate, and factor share of input j, while $\rho_f = \frac{\sigma_f - 1}{\sigma_f}$ is the inputs substitution parameter.

The nominal demand for an additional input is then:

$$H^d_{j,f,t+1} = \mathbb{E}_{f,t}\left[P_{j,t+1}\right]\left[\left(\frac{A_{j,f,t+1}\psi_{f,t+1}}{\mathbb{E}_{f,t}[P_{j,t+1}]}\right)^{\sigma_f} Q^*_{f,t+1} - (1-\delta_j)X_{j,f,t}\right] \quad \forall j = 1,\ldots,J, \tag{7}$$

where the expected marginal costs are:

$$\psi_{f,t+1} = \left[\sum_{j=1}^{n}\left(\mathbb{E}_{f,t}\left[P_{j,t+1}\right]\right)^{1-\sigma_f}\left(A_{j,f,t+1}\right)^{\sigma_f}\right]^{\frac{1}{1-\sigma_f}}. \tag{8}$$

If expected direct costs exceed internal liquidity, firms attempt to borrow in a decentralized credit market. Under credit rationing, firms instead set the optimal input demand that maximizes attainable production.

Endogenous growth. We introduce an endogenous growth process in which firms' labor productivity hinges on workers' skills accumulation through learning by doing, which in turn depends on their individual employment status (Dosi et al., 2018).

The evolution of the skill level s of an individual worker w employed at firm f at time t is given by:

$$s_{w,f,t} = s_{w,f,t-1}\left(1 + \bar{g}\cdot \ell_{w,f,t-1}\right), \tag{9}$$

where $\ell_{w,f,t-1} \in [0,1]$ denotes the worker's labor supply (hours) in the previous period and $\bar{g}$ is a sensitivity parameter. The growth in the average skill level of workers, $\bar{s}_{f,t}$, at each firm f is:

$$\zeta^{\text{growth}}_{f,t} = \frac{\bar{s}_{f,t}}{\bar{s}_{f,t-1}} - 1, \tag{10}$$

with $\bar{s}_{f,t}$ equal to:

$$\bar{s}_{f,t} = \frac{1}{N^w_{f,t}} \sum_w s_{w,f,t}. \tag{11}$$

where $N^w_{f,t}$ is the number of workers at firm i at time t.

Thus, productivity grows endogenously driven by the average skill level growth, as follows:

$$A_{f,j,t} = A_{f,j,t-1} \left(1 + \zeta^{\text{growth}}_{f,t}\right)^{\rho_f}, \quad \text{with } j \in \{L, F\}. \tag{12}$$

The presence of asymmetric information in the labor market prevents firms from accurately assessing workers' skills prior to employment. However, during lay-offs, firms tend to dismiss low-skilled workers first, as their relative performance becomes clearer over time.[3]

Clean and dirty energy plants. We expand the energy sector by incorporating a diversified energy mix, allowing heterogeneous energy firms to invest in dirty or clean plants based on their relative profitability, consistent with the theory of directed technical change (Acemoglu et al., 2012). Firms produce energy services using either brown or green plants, each characterized by specific features such as duration, input requirements, cost structure, and pollution intensity. All firms engage in R&D to enhance plant productivity and competitiveness, thus reducing unit cost and (bid) price. Specifically, firms can allocate a constant fraction σ^{RD} of their profits to R&D expenditures:[4]

$$RD^e_{f,t} = \max(\sigma^{RD} \cdot \Pi_{f,t}, 0) \tag{13}$$

Innovation is a stochastic process, with the probability of innovation, $\mathrm{Pr}^e_{f,t}$, depending on the scale of real R&D investment. If successful, the productivity of the innovative firm increases by γ^E:

[3] Such an endogenous growth process, driven by learning by doing and workers' skill accumulation, allows for the analysis of the growth-versus-level effects of climate change, as unemployment induced by climate damages hampers skill accumulation, thereby reducing potential output. However, this will be the subject of future research.

[4] To ensure the stock-flow consistency of the model the R&D expenditures are redistributed as wage premiums to workers of the same firm proportionally to their skill level. This allows to avoid postulating an external R&D sector.

$$A_{f,t} = \begin{cases} A_{f,t-1} \cdot \left(1+\gamma^E\right)^{\rho_f} & \text{with } \Pr^e_{f,t} = 1 - \exp(\zeta \cdot RD^e_{it}) \\ A_{f,t-1} & \text{otherwise.} \end{cases} \tag{14}$$

Once a plant reaches its maximum life cycle, firms can choose to either maintain the same plant type or switch to a different one, depending on the relative net profitability of clean versus dirty technologies:

$$\Pi_t^{REL} = \frac{\bar{\Pi}_t^{Clean}}{\bar{\Pi}_t^{Clean} + \bar{\Pi}_t^{Dirty}} > \text{rand}() \tag{15}$$

where $\bar{\Pi}_t^{Clean}$ and $\bar{\Pi}_t^{Clean}$ represent the average profits of energy firms adopting clean and dirty, respectively, plants over the last two years.

Electricity market. To enhance the representation of the energy sector, we implement a decentralized electricity market operating on a merit-order basis and introduce differentiated time periods, capturing both peak (day) and off-peak (night) hours.[5] In the electricity market, heterogeneous energy firms submit price-quantity bids, which are sorted by price to form the energy supply curve, with the market price determined by the system marginal price — the cost of the marginal power plant needed to meet total demand.

The market thus operates in two stages, each reflecting distinct demand levels during night and day hours. In the first stage, representing low demand, 40% of the total budget is allocated to energy demand. Suppliers are ranked by price to construct a merit order, and the marginal price is set at the intersection of cumulative supply and total demand. If demand exceeds supply, the highest price becomes the marginal price. Market exchanges then occur, with demand-side agents randomly selected to interact with suppliers ranked by price. Transactions are executed based on available budgets and supply, updating deposits, revenues, and quantities for both parties. The second stage follows the same process but represents high demand, allocating the remaining 60% of the budget.

This market design strengthens competition by encouraging firms to submit lower price bids, increasing infra-marginal rents that can be reinvested

[5] A stream of literature presented detailed ABM depictions of electricity markets from a partial equilibrium perspective; see Nicolaisen et al. (2001), Weidlich and Veit (2008), Sensfuß et al. (2008) and Guerci and Sapio (2012).

in R&D improve efficiency. This feedback loop between profitability, productivity, and competitiveness can create path-dependent dynamics in the energy sector, potentially leading to outcomes ranging from dirty technological lock-in to a clean energy transition, or unstable intermediate trajectories.

3. Calibration and simulation setup

Calibration. The model is calibrated following the procedure described in Bazzana et al. (2024). Table 1 summarizes the key parameters related to the expanded energy sector, representing significant innovations in our model. The remaining parameters can be found in Table C.7 in the Appendix, which also includes a section on empirical validation (see Appendix D).

Variable	Description	Value (Source)
$\theta_{c,2000}$	Initial share of clean E-firms	15% (IEA, 2005)
T_c, T_d	Lifecycle of clean-dirty plants (years)	25, 35 (IEA, 2020)
ψ_{gap}	Clean-dirty cost gap	62% (IEA, 2005)
γ^E	E-firms productivity growth	0.05% (Eurostat)
σ^{RD}, ζ^{RD}	R&D intensity and probability	10%, 10% (Eurostat, ORBIS)
$A_{N,Ec}, A_{K,Ec}$	Factor shares (clean E-firms)	0.2, 0.8 (JEDI NREL)
$A_{N,Ed}, A_{K,Ed}, A_{O,Ed}$	Factor shares (dirty E-firms)	0.28, 0.33, 0.39 (I-O Eurostat)

Table 1: Energy sector parameters

The calibration of green energy firms' characteristics is primarily based on data from the International Energy Agency (IEA), focusing on the distribution and attributes of brown and green firms in the year 2000, which serves as the starting point for our simulation. During this period, the share of clean energy production in the EA was approximately 15%, a figure that we use to establish the initial fraction of green energy firms in our model. At that time, most green energy generation technologies were not competitive with fossil fuels. To account for this disparity, we define an initial exogenous clean-dirty cost gap, denoted as ψ_{gap}, by averaging USD/MWH costs for a sample of countries in 2005 (IEA, 2005). By comparing a bundle of fossil fuels (coal and gas) to a set of renewable generation technologies (hydro, solar, and wind), we find an aggregate cost gap of 62%. Additionally, the operational lifespan of the technologies differs, with brown energy plants averaging ten more years of operational life compared to their green counterparts (IEA, 2021).

The input factor shares for brown firms were calculated following the methodology outlined in Bazzana et al. (2024), using Eurostat Input-Output

(I-O) tables for the Euro Area. In contrast, the calibration of coefficients for green energy firms required a different approach due to the lack of I-O tables with the necessary level of subsector granularity. We retrieved detailed expenditure figures for each type of renewable energy from a specialized disaggregated I-O model known as The International Jobs and Economic Development Impacts (JEDI), developed by the National Renewable Energy Laboratory (NREL). The top five available technologies—wind turbines, hydroelectric, photovoltaic, geothermal, and concentrated solar—were selected for analysis. For each technology, coefficients were evaluated by classifying expenditure figures into labor (e.g., personnel) and capital (e.g., equipment) shares relative to total selected costs.[6] The final coefficient values were derived by calculating the weighted average based on the electricity generation figures for the five selected technologies, expressed in billions of kilowatt-hours.

The low and high demand segmentation of the energy market reflects the typical day-night allocation observed in electricity markets. This segmentation assigns a fixed share of 40% to low demand and 60% to high demand, based on data from the Monthly Hourly Load Values dataset provided by ENTSO-E.

The calibration of R&D parameters yields an average research intensity of 1.5% for energy firms. At first glance, this figure may seem high relative to the European economy. For comparison, Business Expenditures for R&D (BERD) as a share of net turnover in the NACE sector D—Electricity, gas, steam, and air conditioning supply—averaged only 0.15% across 23 European countries in 2021 (Eurostat). However, this calibration is consistent with an analysis of ORBIS data, which indicates that R&D costs relative to operating revenues in large companies within NACE 351 (production, transmission, and distribution of electric energy) stood at 1.67% in 2020. This alignment reflects the reduced number of firms modeled compared to real-world data and more accurately captures future trends in R&D investment in light of increasing demands for energy security in the Euro Area.

Policy Experiment Design. We conduct policy experiments to evaluate interventions for accelerating the green transition. The scenarios are:

[6]Some technologies exhibit multiple operating modes, such as fixed mounts versus single-axis tracking for photovoltaic systems. In these cases, coefficients were calculated for each mode, with the average value used in the final analysis.

1. Baseline with no policy (NP);
2. Brown Tax (BT), imposing a tax on brown firms' profits;
3. Brown Tax and Green Subsidy (BT + GS), using BT revenues to subsidize clean firms;
4. Brown Tax and Conditional Green Subsidy (BT + CGS), where the subsidy depends on R&D investments by green firms.

In the baseline scenario, the plant ages of clean firms are initialized to 1 in the year 2000, while the plant ages of dirty firms are drawn from a uniform distribution, $U(0, T_d)$.[7] For each scenario, we consider three levels of policy intensity, defined by the brown tax rate: low (25%), medium (50%), and high (75%). To ensure robustness, for each policy scenario we perform 200 Monte Carlo simulations with different random seeds, reporting the mean outcomes along with standard deviation and 75-95% confidence intervals.

4. Simulation results

4.1. Likelihood of green transition

Figure 2 illustrates the evolution of the share of green energy firms from 2000 to 2100 across Monte Carlo simulations under the baseline scenario with no policy intervention. Simulations are categorized into three groups based on the proportion of clean energy firms $\theta_{c,2100}$ at the end of the century: Brown ($\theta_{c,2100} < 1/3$), Intermediate ($1/3 < \theta_{c,2100} < 2/3$) and Green ($\theta_{c,2100} > 2/3$). These categories are represented by red, yellow, and green lines, respectively.

The results show that, in most simulations, the share of green firms jumps to zero by 2025, indicating that the energy sector locks into brown technology relatively quickly. This occurs because, in the absence of policy intervention, green firms tend to switch to more profitable brown plants, which further consolidate their initial cost advantage through path dependence. While some simulations show the economy achieving a green energy transition without intervention, Table 2 reveals this occurs with only a 19.5% probability (first line, NP scenario). Thus, there is a nearly 80.5% chance of failing to achieve a green transition without policy measures, highlighting the need for policy action.

[7] To avoid confounding effects, we include a 40-period burn-in phase, allowing the model to stabilize and mitigating the disruptive impacts of the sudden, exogenous entry of clean firms.

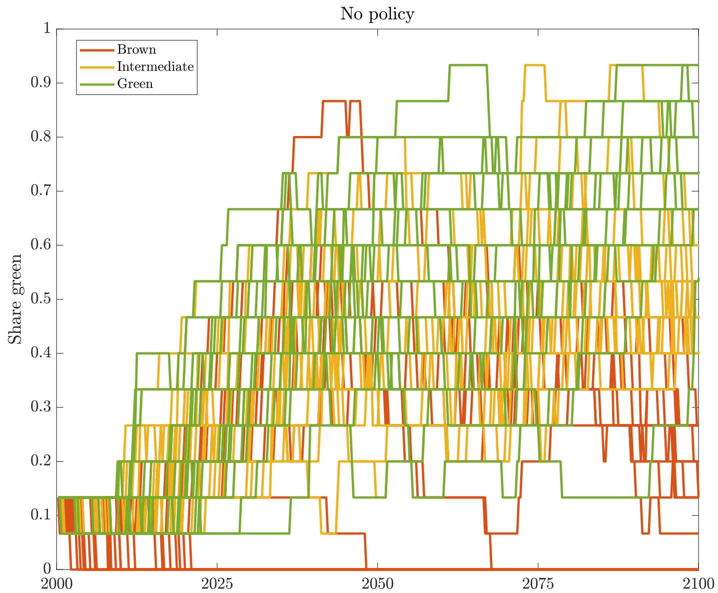

Figure 2: Share of green firms in the energy sector across 200 Monte Carlo simulations over time under no policy scenario. Simulations are categorized into three groups - brown, intermediate, and green —- based on the proportion of green firms at the end of the century.

Figure 3 shows the evolution of the share of green energy firms over time across Monte Carlo simulations under alternative policy scenarios at various intensity levels. Table 2 summarizes the results in terms of transition probabilities - i.e., the proportion of simulations resulting in Brown, Intermediate or Green outcomes - and GDP loss at the end of the century, defined as mean percentage changes in real GDP at century's end relative to the no-policy scenario, with standard deviations in parentheses.

We can see that Brown Tax (BT) alone increases the likelihood of green transition as intensity rises, reaching 57% probability at high intensity. The combination of Brown Tax and Green Subsidies (BT+GS) yields mixed results, with high intensity surprisingly favouring the intermediate outcome over the green transition. Notably, the combination of Brown Tax and Conditional Green Subsidies (BT+CGS) proves the most effective, especially at high intensity, reducing the probability of brown lock-in to less than 30%.

These results suggest that both the types of policy interventions and

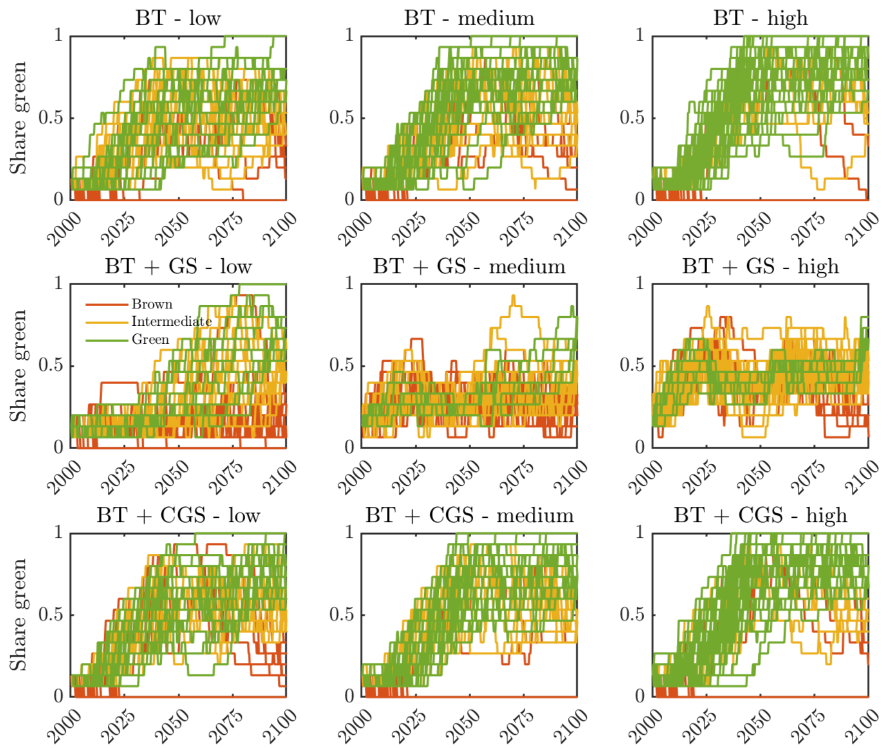

Figure 3: Share of green firms in the energy sector across 200 Monte Carlo simulations over time under alternative policy scenarios. Simulations are categorized into three groups - brown, intermediate, and green —- based on the proportion of green firms at the end of the century.

their design can significantly influence transition dynamics. While some combinations are more effective than others in advancing a shift towards low-carbon technology, conventional policies show limited effectiveness in fostering a green transition. The best-case scenario is the combination of a brown tax with a green subsidies linked to R&D (BT+CGS), with a 58.6% probability of a green transition. In contrast, the worst-case scenario occurs when BT revenues fund an unconditional green subsidy (BT+GS), where the probability drops to less than 10%.

Experiment	Transition Probability			GDP Impact		
	Brown	Intermediate	Green	Brown	Intermediate	Green
No Policy	0.483	0.322	0.195	-	-	-
BT - low	0.448	0.333	0.218	0.059	-0.071	-0.121
				(0.433)	(0.155)	(0.312)
BT - medium	0.391	0.241	0.368	0.056	-0.109	-0.202
				(0.136)	(0.323)	(0.411)
BT - high	0.322	0.103	0.575	0.050	0.125	-0.272
				(0.143)	(0.301)	(0.401)
BT+GS - low	0.575	0.299	0.126	-0.316	-0.193	-0.190
				(0.411)	(0.265)	(0.291)
BT+GS - medium	0.598	0.333	0.069	-0.630	-0.623	-0.439
				(0.317)	(0.297)	(0.233)
BT+GS - high	0.241	0.655	0.103	-0.744	-0.771	-0.827
				(0.186)	(0.206)	(0.122)
BT+CGS - low	0.471	0.253	0.276	0.045	-0.143	-0.041
				(0.388)	(0.228)	(0.185)
BT+CGS - medium	0.391	0.276	0.333	0.066	-0.105	-0.127
				(0.222)	(0.251)	(0.522)
BT+CGS - high	0.299	0.115	0.586	0.044	-0.115	-0.193
				(0.205)	(0.238)	(0.457)

Table 2: Effects of policy experiments on transition probability and economic impacts under Brown, Intermediate, and Green transition scenarios. Transition probability is the proportion of simulations falling into each category. GDP impact is the percentage variation of average real GDP relative to the no-policy scenario, with standard deviations in parentheses.

4.2. Macroeconomic effects of green transition

Focusing on the last column in Table 2, we observe that the green transition tends to exert long-term adverse effects on the economy, with GDP loss intensifying as policy strength increases, in line with Ponta et al. (2018). The BT+GS policy mix, especially at medium-high intensities, imposed the most pronounced economic costs across all transition scenarios. In comparison, the BT alone and BT+CGS policies also generate negative effects, though their impacts are relatively smaller.[8] Notably, an intermediate transition is more

[8]While these GDP losses might appear large, two considerations are crucial. First, given the endogenous nature of technical change, even a minor reduction in GDP growth

economically harmful than either a complete green transition or remaining in a brown lock-in scenario.

The poor performance of conventional transition policies, particularly the BT+GS, in both transition likelihood and economic costs is somewhat striking, underscoring the need for a deeper analysis of the macro-financial risks associated with the energy transition.

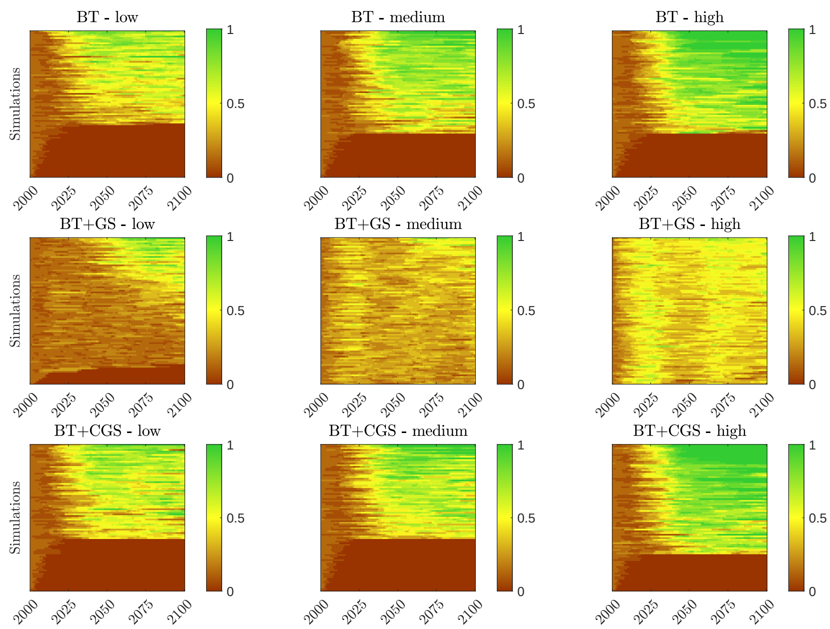

Figure 4: Share of green firms over time across 200 MC simulations clustered by similarity.

rates over a few periods can yield substantial differences in GDP levels in the long term. Specifically, the average annual GDP growth rate is 3.45% in the no-policy (brown lock-in) scenario, compared to 3.42% under the BT+CGS policy (green transition, high intensity), a mere 0.03% annual difference. This difference accumulates to a 19.3% GDP loss by century's end under BT+CGS relative to the no-policy scenario, as shown in Table 2, equivalent to five years of forgone growth. Second, interpreting this outcome as a GDP "loss" may be misleading, as it reflects a comparison with an idealized baseline that assumes no climate shocks. If climate impacts were accounted for, the economic trade-offs observed here might diminish. However, since the model is calibrated to the Euro Area, we exclude climate shocks, as their full impact depends on global policy responses beyond the Euro Area's control.

4.2.1. Puzzle 1: Failure of the BT + GS policy mix

The first key factor influencing the effectiveness of the BT+GS policy is the speed of transition during the initial phases of the simulation. By directly affecting the relative profitability channel (15), the unconditional green subsidy amplifies the effects of the brown tax, accelerating the switch to green technologies. This is illustrated in Figure 4, which displays the evolution of the share of green firms over time, shown as heatmaps based on clustered simulations across different policy types and intensities.

We observe that while the share of green firms steadily increases and stabilizes under BT and BT+CGS, it rises more rapidly in all simulations under the BT+GS policy but often reverts to brown technologies, eventually becoming locked in an intermediate outcome.

The second key factor concerns the competitiveness of the green technology at different stages of the transition. Figure 5 shows the effects of different policy interventions on the relative unit cost of green and brown technologies (left panel) and the profits for brown energy firms as a share of GDP (right panel) for the period 2000-2050.[9]

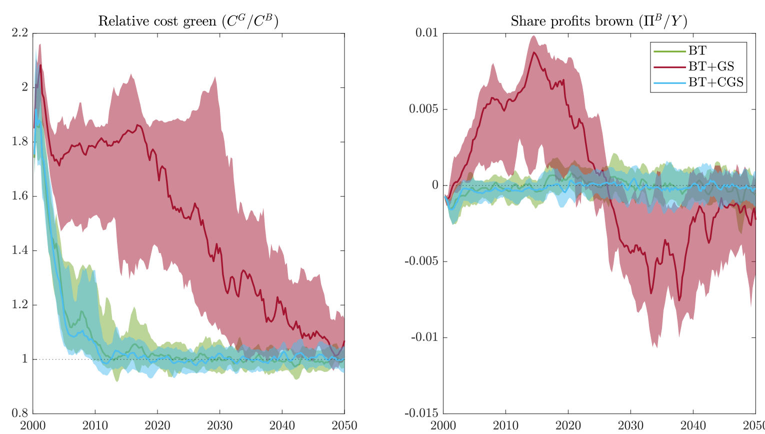

Figure 5: Average relative cost and profitability of green and brown energy firms under different policies scenarios. Results show the mean and confidence intervals from green transition simulations outcome for each policy scenario.

[9]This analysis focuses on the green scenario, including simulations where the share of green firms exceeds two-thirds, $\theta_{c,2100} > 2/3$.

It can be seen that BT (green line) and the BT+CGS (blue line) policies are effective in quickly reducing the relative cost of green technology, achieving near “grid parity"[10] with brown technology by around 2010-2015. In contrast, under BT+GS (red), green costs remain high by around 2030-2035, gradually converging to the brown costs by 2050. The right panel shows that, while BT and BT+CGS policies reduce brown firms' profits by making green technologies relatively more competitive, brown firms' profits steadily increase for an extended period under BT+GS, hence weakening firms' incentives for adopting clean technologies, despite policy support. By boosting green tech profitability without R&D conditionality, the BT+GS policy leads to a rapid but unsustainable shift to less competitive green technologies. This results in a quick rise in the share of green firm (as shown in Figure 4), but also allows brown firms to gain infra-marginal rents on the electricity market, potentially reversing the transition. Nonetheless, the prolonged high tax on brown firms prevents a full lock-in to brown technology, resulting in an intermediate outcome that is economically unsustainable (Table 2).

4.2.2. Puzzle 2: Macro-financial risks related to energy transition

To highlight the key mechanisms underlying the economic dynamics during the energy transition, we examine key sectoral variables from the BT + CGS scenario at high intensity, which delivers the best overall outcomes.

Figure 6 illustrates percentage changes in production, excess demand and price across industrial sectors (columns), comparing brown and green transition outcomes relative the baseline scenario without policy. These plots provide insights into the sectoral imbalances and production constraints that contribute to the broader economic challenges associated with the transition.

In the early stage, energy production declines significantly as brown firms exit the market due to high tax on dirty plants (see brown defaults in Figure 7) and green firms adopt a technology that is not mature yet, reducing overall production capacity. This creates excess demand in the energy services market, intensifying production bottlenecks. The resulting energy shortage forces downstream firms, including capital and consumption goods producers, to curtail their supply. At the same time, the capital market experiences

[10]The concept of grid parity in this context should be understood broadly as a competitiveness indicator, rather than in its strict technical sense. For a more comprehensive exploration of the grid parity concept and its implications, refer to Choi et al. (2015) and Nissen and Harfst (2019).

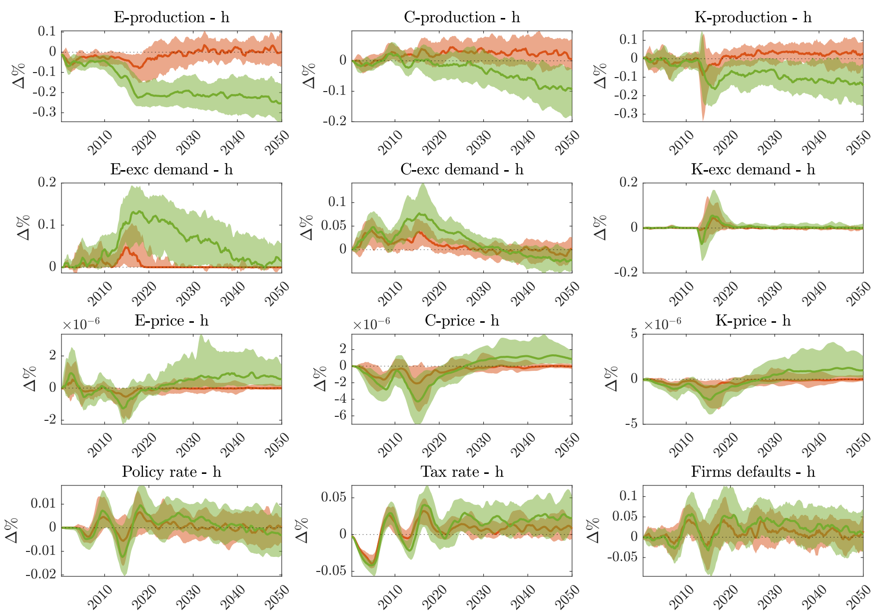

Figure 6: Key variables for the energy (E), consumption (C) and capital (K) sectors under BT + CGS policy (high intensity) comparing Brown and Green simulation outcomes. Results show the mean and confidence intervals from 200 Monte Carlo simulations.

a surge in excess demand. This reflects the rising capital demand of energy firms transitioning to capital-intensive green technologies, which cannot be met by capital producers constrained by energy shortages.

Following an initial decline, price levels rise across sectors due to persistent market imbalances, as shown in Figure 6. In response, political authorities adjust macroeconomic policies endogenously. The central bank raises the policy rate, following the Taylor rule, to mitigate inflationary pressures. Concurrently, the higher interest payments on public debt compel the government to raise tax rates in order to maintain debt sustainability. These policy adjustments, combining higher interest and tax rates, further strain firms' financial conditions, resulting in higher default rates.

Focusing on the energy sector, Figure 7 illustrates the dynamics of key variables for brown and green energy firms, aggregated across individual firms in each category, alongside the evolution of the share of green firms in the energy sector (dashed blue line, right axis) for one representative simulation

Figure 7: Evolution of capital, labour, fossil fuel usage, loans, net worth and cumulative defaults for energy green and brown firms, aggregated across firms, from 2000 to 2050 in a representative simulation based on the BT+CGS policy scenario (medium intensity). The dashed blue line shows the share of green firms in the energy sector (right axis).

under the BT+CGS policy scenario. As shown, the policy increases the relative competitiveness of clean technology (Figure 5), leading to a rise in capital investment and labor employed by green firms, while labor, capital, and fossil fuel usage by brown firms decline. Green firms take on additional debt to finance the investment surge, while their net worth rises due to increased profitability. By contrast, the policy negatively affects brown firms, reducing profitability and net worth, resulting in higher default rates.

These dynamics underscore the importance of carefully managing the energy transition to avoid bottlenecks in key sectors, which can exacerbate economic disruptions during the shift to green technology. The results suggest that conventional transition policies, such as a brown tax combined with green subsidies, may not be sufficient to ensure a smooth transition. While these policies can incentivize green technology adoption, they often fail to address the production-financial constraints and capital shortages that emerge in key industries. As seen, excess demand in both energy and capital markets can lead to widespread production slowdowns across sectors reliant on these inputs. As pointed out by Cervantes et al. (2023), without more targeted policies – such as those focusing on green innovation and industrial capacity – the transition risks amplifying sectoral imbalances, thereby limiting the overall effectiveness of conventional measures and heightening the macroeconomic costs of the green shift.

Experiment	Transition Probability			GDP Impact		
	Brown	Intermediate	Green	Brown	Intermediate	Green
BT+CGS - low	0.471	0.253	0.276	0.045	-0.143	-0.041
				(0.388)	(0.228)	(0.185)
BT+CGS - medium	0.391	0.276	0.333	0.066	-0.105	-0.127
				(0.222)	(0.251)	(0.522)
BT+CGS - high	0.299	0.115	0.586	0.044	-0.115	-0.193
				(0.205)	(0.238)	(0.457)
BT+CGS+MP - low	0.437	0.172	0.391	-0.155	-0.289	-0.351
				(0.304)	(0.161)	(0.149)
BT+CGS+MP - medium	0.299	0.207	0.494	-0.201	-0.291	-0.430
				(0.202)	(0.390)	(0.184)
BT+CGS+MP - high	0.207	0.034	0.759	-0.181	-0.532	-0.446
				(0.149)	(0.134)	(0.293)

Table 3: Effects of BT+CGS+MP policy on transition probabilities and real GDP. Transition probability represents the distribution of Brown, Intermediate, and Green outcomes across 200 MC simulations. GDP impact is average percentage variation of real GDP relative to the no-policy scenario in 2100, with standard deviations in parentheses.

4.3. Possible answers (I): Coordinated monetary policy

The central bank's monetary policy, guided by the standard Taylor rule, does not account for the specific economic and financial challenges posed by the green transition. A coordinated monetary policy could mitigate the adverse effects of sectoral imbalances and inflationary pressures by aligning central bank actions with fiscal measures, thereby stabilizing financial conditions and reducing default risk. Recent efforts have explored the potential for such coordination, highlighting its importance in addressing environmental challenges (Chan et al., 2024).

To explore this, we implement the BT+CGS transition policy with a more cautious and asymmetric monetary stance. Specifically, the central bank refrains from raising interest rates - despite the Taylor rule implying otherwise (A.4) - whenever the share of green energy firms is below two-thirds, thereby biasing interest rates downward and improving financial conditions for investment.

Table 3 presents the effects of the combined environmental and coordinated monetary policy (BT+CGS+MP) on transition probabilities and GDP for varying policy intensities. To facilitate comparison, the top section reports the outcomes of conventional environmental policy alone (BT+CGS).

The results indicate that coordinated monetary policy significantly increases the probability of achieving a green transition, especially at higher policy intensities, with success rates jumping to 76%. However, this comes at the expense of a considerable GDP loss. By creating more favourable financing conditions, the central bank can indeed facilitate the adoption of green technologies. Yet, while transition probabilities improve, the persistent economic downturn suggests that underlying production bottlenecks remain unresolved, underscoring the need for additional policy interventions.

4.4. Possible answers (II): Green industrial policy + green finance

In Figure 6, the decline in energy production during the transition is shown to be accompanied by excess demand in capital markets, as energy firms face bottlenecks when switching to capital-intensive green technologies. Capital, in this context, functions as a critical intermediate input for the production of clean technologies, yet it takes time to be produced and can remain in short supply – similar to key inputs like microchips, which also face production limitations and supply constraints (Trippl et al., 2024).

To alleviate such production constraints, we implement a green industrial policy (GIP) that temporarily boosts capital production by providing subsidies to capital producers.[11] The policy is activated for a specified period around the introduction of green energy firms ($\tau^{GIP} = 50$, roughy 10 years), easing constraints on the adoption of clean technologies. Under GIP, capital firms increase their desired production by a fixed target growth rate ($\rho^{GIP} = 0.1\%$), with the government covering the additional production costs.

Additionally, we implement a green finance (GF) version of GIP. During the same period that GIP is in place, banks reduce the firm-specific interest rate to zero for capital good producers, leaving only the bank-specific and system risk components (A.3) , thereby providing targeted financial support

[11]The term “green" highlights that the industrial policy aims to expand the production capacity of an intermediate input crucial for clean technologies, similar to the CHIPS Act in the U.S. (Luo and Van Assche, 2023).

Experiment	Transition Probability			GDP Impact		
	Brown	Intermediate	Green	Brown	Intermediate	Green
BT+CGS - low	0.471	0.253	0.276	0.045	-0.143	-0.041
				(0.388)	(0.228)	(0.185)
BT+CGS - medium	0.391	0.276	0.333	0.066	-0.105	-0.127
				(0.222)	(0.251)	(0.522)
BT+CGS - high	0.299	0.115	0.586	0.044	-0.115	-0.193
				(0.205)	(0.238)	(0.457)
BT+CGS+GIP - low	0.276	0.069	0.655	-0.033	0.026	-0.166
				(0.232)	(0.313)	(0.394)
BT+CGS+GIP - medium	0.241	0.149	0.609	0.006	0.032	-0.178
				(0.215)	(0.672)	(0.345)
BT+CGS+GIP - high	0.253	0.230	0.517	0.052	-0.005	-0.177
				(0.449)	(0.251)	(0.291)
BT+CGS+GIP+GF - low	0.276	0.080	0.644	0.002	0.023	-0.179
				(0.264)	(0.290)	(0.396)
BT+CGS+GIP+GF - medium	0.241	0.161	0.598	0.028	-0.064	-0.183
				(0.212)	(0.342)	(0.342)
BT+CGS+GIP+GF - high	0.241	0.207	0.552	-0.004	-0.010	-0.134
				(0.227)	(0.259)	(0.409)

Table 4: Effects of conventional transition policy (BT+CGS) coupled with green industrial policy (GIP) and green finance (GF) on transition probabilities and GDP. Transition probability represents the distribution of Brown, Intermediate, and Green outcomes across 200 MC simulations. GDP impact is average percentage variation of real GDP relative to the no-policy scenario in 2100, with standard deviations in parentheses.

to firms involved in the GIP program. This coordinated effort aims to alleviate financial constraints on capital producers, enhancing the effectiveness of the green industrial policy in facilitating the energy transition.

From Table 4 we can see that green industrial policy significantly raises the probability of achieving a green transition, particularly under low-intensity environmental policy (BT+CGS), without exacerbating – and in some cases mitigating – the associated macroeconomic costs. When combined with green finance (GF), the results improve further, showing higher transition probabilities with similar or slightly reduced GDP losses, especially at high intensity.

To conclude, Figure 8 provides an overall comparison of policy interventions for varying intensity levels, illustrating the trade-off between environmental benefits, measured by the probability of green transition (vertical axis) – i.e., the portions of simulations resulting in a high share of green firms – and economic costs, represented by GDP loss (horizontal axis). This

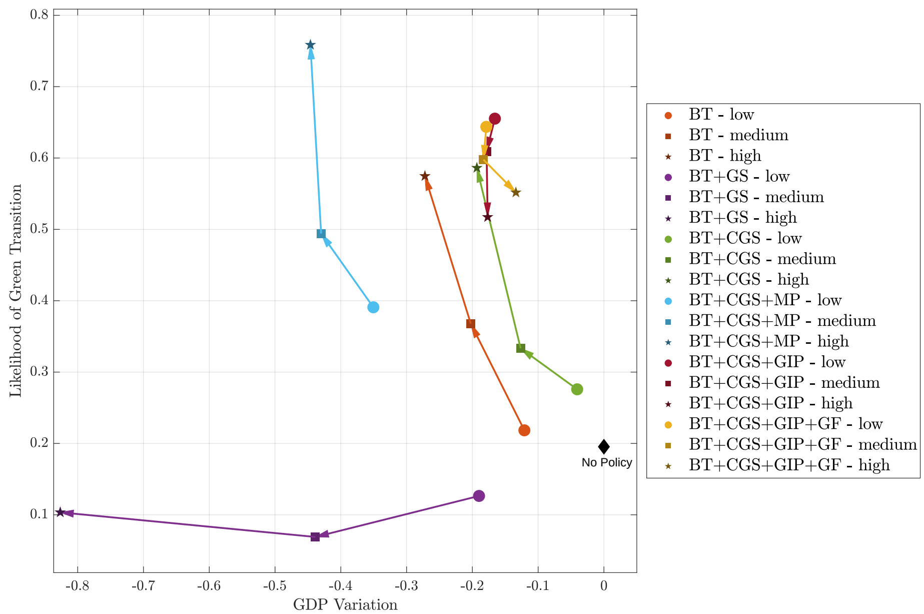

Figure 8: Impact of policies on GDP loss and likelihood of green transition across all scenarios, grouped by policy type and intensity. Arrows indicate increasing policy intensity within the same policy type.

comparison highlights the balance between fostering green transition and minimizing macroeconomic disruptions.

The top-right corner represents the ideal outcome for policy makers, where a high transition probability is associated with limited GDP losses. Conversely, moving from the top-right to the bottom-left reflects a worsening scenario, with low green shares and high economic damages. Moving from the bottom-right to the top-left suggests a trade-off between environmental benefits and economic harm.

As expected, the BT+GS policy (purple line) performs the worst: higher policy intensity leads to lower green shares and greater economic damages. Both BT (orange) and BT+CGS (green) policies, exhibit a clear trade-off between environmental outcomes and economic costs: at low intensities, transition probabilities and economic losses are relatively low, but they rise sharply with increased intensity. However, BT is strictly dominated by BT+CGS, as the latter is positioned further to the upper-right.

While the coordinated monetary policy (BT+CGS+MP, light blue) improves the green transition probability, it fails to break the trade-off, as higher green shares still come with significant economic harms. The best outcomes are achieved by the lowest intensities of the policies incorporating GIP and GIP+GF, represented by the cluster of points in the top-right corner, indicating the ideal balance of high transition probability and low GDP loss. Notably, these policy mixes display limited variability across policy intensity, suggesting that, when combined with a green industrial policy, even moderate levels of brown tax and conditional green subsidies are sufficient to ensure a smooth transition.

5. Concluding remarks

This paper evaluates the effectiveness of various policy interventions in facilitating an orderly energy transition and mitigating associated macro-financial risks through the Multi-Agent model for Assessing Transition Risks (MATRIX), an agent-based integrated assessment model for the EA.

The extended MATRIX model integrates endogenous growth, directed technical change driven by R&D efforts of energy firms, and heterogeneous energy generation technologies that encompass both fossil fuel and renewable energy plants. Furthermore, the model offers a realistic representation of the energy services market, closely mirroring the structure and dynamics of real-world electricity markets.

Assuming realistic differences in efficiency and technological maturity across energy technologies, we find that a spontaneous green transition is improbable ($\leq 20\%$). This is in line with Lamperti et al. (2020), although one remarkable difference is that in our work even without policy 32% of the simulations do not fall in a lock-in, being here classified as intermediate.

The introduction of green transition policies, including taxes on fossil fuel firms and green subsidies, results in an increase in the share of green firms; however, this shift is accompanied by GDP losses (spanning from -4% to -19%). The effectiveness of these policies varies depending on their design and intensity, with unconditional green subsidies leading to suboptimal outcomes. This contrasts Ponta et al. (2018), as here even policies with lower intensities can result in GDP losses. These results highlight how the transition to clean energy technologies can create significant sectoral imbalances and production bottlenecks, particularly in the energy and capital goods sectors. These imbalances can propagate through the economy, leading to widespread production slowdowns and inflationary pressures.

Coordinated policies provide further insights. A more accommodative monetary stance can significantly increase the likelihood of achieving a green transition when combined with a brown tax and green R&D subsidy, albeit at the cost of increased GDP loss. Green industrial policies aimed at expanding the production capacity of capital goods can mitigate critical bottlenecks and improve transition outcomes without exacerbating economic costs. Moreover, additional benefits can be realized by integrating these policies with green finance initiatives, such as lowering loan costs for the capital sector. This agrees with findings by the literature on the appropriateness of policy mixes, as highlighted by Nieddu et al. (2024).

This work has several limitations. First, technology is represented in a simplified manner, encompassing only two energy technology types. This simplification may overlook the nuances associated with a broader range of technologies in both the dirty and clean sectors. Additionally, critical aspects of renewable energy, such as intermittency, are not addressed in this analysis. Furthermore, the market for energy firms is oversimplified compared to real-world electricity markets, which typically operate on a day-ahead basis and involve additional complexities, including zonal pricing and balancing markets (Guerci and Sapio, 2012). Lastly, the model assumes a closed regional area, which may limit the applicability of the results, particularly regarding issues like capital shortages that could be influenced by trade dynamics.

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Appendix A. The MATRIX model

Appendix A.1. Overview

This Appendix offers a concise description of the core components in the original MATRIX model. For a more comprehensive analysis, refer to Ciola et al. (2023); Turco et al. (2023); Bazzana et al. (2024).

The MATRIX model portrays an economy comprising diverse agents: households, firms, banks, an exogenous fossil fuel sector, a central bank, and a government. Households ($h = 1, \ldots, \mathcal{N}^H$) are categorized as workers ($\mathcal{N}^W$), entrepreneurs ($\mathcal{N}^F$) (each owning a single firm), or bankers ($\mathcal{N}^B$) (owning a single bank). Firms ($f = 1, \ldots, \mathcal{N}^F$) operate in three sectors: energy services (E), consumption goods (C), and capital goods (K). The banking sector consists of ($b = 1, \ldots, \mathcal{N}^B$) banks.

Agents interact within markets through a decentralized search and matching mechanism. Demand units seek supply units, with those offering larger quantities at lower prices having higher probabilities of selling. This decentralized approach can lead to unfulfilled demand or excess supply. Agents adapt their consumption and production strategies in response to matching frictions and evolving economic conditions, influencing macroeconomic dynamics and potentially triggering cycles, fluctuations, and recessions. The following sections detail the event sequence and summarize the agents' behavioral equations.

Appendix A.2. Sequence of Events

The model follows this sequence of events:

1. Growth levels based on previous turn skills accumulation is set.
2. Firms enter with predetermined levels of production, selling prices, and input demands from the previous period.[12]
3. Production factor markets open:
    i. Labor market: Workers supply waged labor (up to one unit) to firms, pay income taxes, and set consumption budgets.
    ii. Fossil fuel market: Firms (e.g. Brown E-firms) purchase energy input from the monopolistic fossil fuel sector.

[12]The system is initialized at the perfect competition steady state solution at $t = 0$.

iii. Energy market: E-firms produce energy services according to their technology, selling to C- and K-firms.

iv. Consumption goods market: C-firms produce consumption goods using capital, labor, fossil fuel, and energy services, selling to households.

v. Capital goods market: K-firms supply capital goods to C- and E-firms, using labor, fossil fuel, and energy services.

4. Expected prices and quantities are updated.
5. Firms calculate profits, taxes, dividends, and outstanding bank debt.
6. Insolvent or illiquid firms unable to be bailed out by their owners default; new firms are initialized.
7. Firms set input demand for the next period based on expectations and resources, potentially accessing the credit market.
8. Banks account for profits and non-performing loans (NPL). Bank default procedures are executed if necessary.
9. The government adjusts tax rates and social transfers according to fiscal sustainability rules.
10. The central bank sets the policy rate based on its Taylor rule.

Appendix A.3. Households behavior

The nominal income $Y_{h,t}$ for households $h = 1, \ldots, \mathcal{N}^W$ is determined by their type:

$$Y_{h,t} = \begin{cases} W_t N_{w,t} & \text{for workers,} \\ DIV_{f,t} - REC_{f,t} & \text{for entrepreneurs,} \\ DIV_{b,t} - REC_{b,t} & \text{for bankers.} \end{cases} \tag{A.1}$$

Workers supply labor ($N_{w,t} \in [0, 1]$) for a uniform salary W_t, which reflects market conditions and inflation expectations. Entrepreneurs and bankers receive dividends $DIV_{h,t}$ and incur recapitalization costs $REC_{h,t}$ if their businesses go bankrupt. The household's consumption budget, $H^d_{h,t}$, is a weighted sum of permanent income $\bar{Y}h, t$ and deposits:

$$H^d_{h,t} = \bar{Y}_{h,t} + \chi D_{h,t}, \tag{A.2}$$

where χ represents the propensity to consume out of financial wealth. The permanent income $\bar{Y}_{h,t}$ is calculated as a weighted average of current net income and past permanent income levels, adjusted for expected inflation.[13]

Appendix A.4. Banking Sector

The banking sector provides credit to firms requiring additional resources for production input purchases. Loan pricing depends on the financial situation of both borrower and lender, as well as a systemic risk component, while loan quantity is determined by capital requirements. The interest rate $i_{b,f,t}$ charged by bank b to borrowing firm f at time t is given by:

$$i_{b,f,t} = i_t^{CB} + \rho^B \frac{L_{f,t}}{NW_{f,t}} + \varrho^B \left(1 - \frac{NW_{b,t}}{\max\limits_{s=1,\ldots,\mathcal{N}^B} NW_{s,t}} \right) + \iota^B \frac{NPL_{t-1}}{L_{t-1}}, \quad \text{(A.3)}$$

where $\rho^B, \varrho^B, \iota^B > 0$ are interest rate-related parameters. The cost of external finance increases with the risk-free policy rate i_t^{CB}, the firm's leverage ratio, $L_{f,t}/NW_{f,t}$, and the non-performing loans ratio, NPL_{t-1}/L_{t-1}. It decreases instead with the bank's net worth, $NW_{b,t}$. Banks must comply with macroprudential capital requirements, in line with the Basel III international regulatory framework. These requirements define two constraints, namely the total amount of credit that banks can extend, and the maximum exposure to a single counterpart. As a result, borrowing firms may be unable to fully satisfy their financing needs. In such cases, they are forced to scale down their desired production and, consequently, their input demand.

Appendix A.5. Central Bank

The central bank determines the risk-free policy rate, i_t^{CB}, using an inertial Taylor rule:

$$i^{CB}t = \rho^{CB} i^{CB} t - 1 + (1 - \rho^{CB}) \max\left[0,\ r^* + p^* + \lambda^y (u^* - u_{t-1}) + \lambda^p (p_{C,t-1} - p^*)\right]. \quad \text{(A.4)}$$

This rule responds to deviations in inflation and unemployment rates from their target levels, p^* and u^* respectively, given the steady-state interest rate r^*. To prevent abrupt changes in firms' financing conditions, the interest rate is adjusted gradually, with ρ^{CB} determining the adjustment speed.

[13] The permanent income is set as a weighted average of current net income and past permanent income levels, updated by expected inflation.

Appendix A.6. Government

The government collects taxes (TAX_t), distributes transfers (TRA_t) to low-income households, and provides liquidity of last resort (EXP_t) to failed banks. When necessary, it issues additional bonds, purchased by the banking sector at the risk-free policy rate (i_t^{CB}). Public debt (B_t) evolves as:

$$B_t = (1 + i_{t-1}^{CB})B_{t-1} + TRA_t + EXP_t - TAX_t. \tag{A.5}$$

The debt-to-GDP ratio dynamics are expressed as:

$$b_{t+1} = \frac{1 + i_t^{CB}}{1 + g_t} b_t - f_{t+1}, \tag{A.6}$$

where b_t is the debt-to-GDP ratio, $f_t \equiv (TAX_t - TRA_t - EXP_t)/GDP_t$ is the primary budget-to-GDP, and g_t is the expected nominal GDP growth rate.

To ensure fiscal sustainability, the government gradually adjusts the current debt-to-GDP ratio to a target value b^* at a rate ρ^G:

$$b_{t+1} = b_t + \rho^G (b^* - b_t). \tag{A.7}$$

Combining (A.7) and (A.6) yields the expected primary balance:

$$-f_{t+1} = \rho^G b^* + (1 - \rho^G) \left[1 - \frac{1 + i_t^{CB}}{(1 + g_t)(1 - \rho^G)} \right] b_t. \tag{A.8}$$

The government sets the tax rate, τ_t^{tax}, to comply with the expected primary balance. The share of social transfer over GDP, τ_t^{tra}, is fixed at a rate ψ^G, but can be increased:

$$\tau_t^{tra} = \max\left(\psi^G, -f_{t+1}\right), \tag{A.9}$$

where ψ^G is the constant benchmark value. This ensures that the expected primary balance provides sufficient fiscal space.

The current period's tax rate is then:

$$\tau_t^{tax} = \max\left(0, f_{t+1} + \tau_t^{tra}\right). \tag{A.10}$$

If negative, the tax rate is set to zero.

Appendix B. Stock-flow consistency

Table B.5: Aggregate balance sheet

	Households	**E-firms**	**C-firms**	**K-firms**	**Banks**	**Government**	**Central Bank**	**Total**
Deposits	$+D_h$	$+D_e$	$+D_c$	$+D_k$	$-D$			0
Capital		$+K_e$	$+K_c$					$+K$
Bonds					$+B_b$	$-B$	$+B_{cb}$	0
Loans		$-L_e$	$-L_c$	$-L_k$	$+L$			0
Reserves					$+H$		$-H$	0
Net worth	$-NW_h$	$-NW_e$	$-NW_c$	$-NW_k$	$-NW_b$	$-NW_g$		$-K$
Σ	0	0	0	0	0	0	0	0

Table B.6: Aggregate transaction flow matrix

	Households	**E-firms**		**C-firms**		**K-firms**		**Banks**		**Fossil fuel**	**Abatement**	**Government**	**Central Bank**	Σ
		CA	KA	CA	KA	CA	KA	CA	KA					
Consumption	$-C$	0	0	$+C$	0	0	0	0	0	0	0	0	0	0
Public Exp.	$+TRA$	0	0	0	0	0	0	$+EXP$	0	0	0	$-G$	0	0
Investment	0	0	$-I_e$	0	$-I_c$	$+I_k$	0	0	0	0	0	0	0	0
Energy	0	$+E$	0	$-E_c$	0	$-E_k$	0	0	0	0	0	0	0	0
Fossil fuel	$+(1-\eta_o)F$	$-F_e+\eta_o F$	0	$-F_c$	0	$-F_k$	0	0	0	$+F(-F)$	0	0	0	0
Wages	$+W$	$-W_e$	0	$-W_c$	0	$-W_k$	0	0	0	0	0	0	0	0
Taxes	$-T_h$	$-T_e$	0	$-T_c$	0	$-T_k$	0	$-T_b$	0	0	0	$+T$	0	0
Loan interests	0	$-iL_e$	0	$-iL_c$	0	$-iL_k$	0	$+iL$	0	0	0	0	0	0
Bonds interests	0	0	0	0	0	0	0	$+i^{CB}B_b$	0	0	0	$-i^{CB}B$	$+i^{CB}B_b$	0
Profits	$+DPr$	$-Pr_e$	$+UPr_e$	$-Pr_c$	$+UPr_c$	$-Pr_k$	$+UPr_k$	$-Pr_b$	$+UPr_b$	0	0	$+i^{CB}B_{cb}$	$-i^{CB}B_{cb}$	0
Stocks:														
Δ Deposits	$-\Delta D_h$	0	$-\Delta D_e$	0	$-\Delta D_c$	0	$-\Delta D_k$	0	$+\Delta D_b$	0	0	0	0	0
Δ Loans	0	0	$+\Delta L_e$	0	$+\Delta L_c$	0	$+\Delta L_k$	0	$-\Delta L_b$	0	0	0	0	0
Δ Bonds	0	0	0	0	0	0	0	0	$-\Delta B_b$	0	0	$+\Delta B$	$-\Delta B_{cb}$	0
Δ Reserves	0	0	0	0	0	0	0	0	$-\Delta H$	0	0	0	$+\Delta H$	0
Δ Total	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Appendix C. Calibration parameters

Table C.7: MATRIX model: economic module parameters

Variable	Description	Value
$\mathcal{N}^W$	Number of workers	1000
β^C	Households discount rate	0.996
ε, χ	Memory parameter, propensity to consume	$\beta^C, 1-\beta^C$
$\mathcal{N}^E, \delta_E, \sigma_E$	Number of E-firms, depreciation, elasticity	$15, 1, 0.25$
$\mathcal{N}^C, \delta_C, \sigma_C$	Number of C-firms, depreciation, elasticity	$100, 1, 0.25$
$\mathcal{N}^K, \delta_K, \sigma_K$	Number of K-firms, depreciation, elasticity	$60, 0.05/4, 0.25$
$A_{N,C}, A_{K,C}, A_{E,C}, A_{O,C}$	Factor shares (C-firms)	$0.69, 0.25, 0.03, 0.03$
$A_{N,K}, A_{E,K}, A_{O,K}$	Factor shares (K-firms)	$0.91, 0.04, 0.05$
β^F, μ^F	Firms discount rate, dividend payout	$0.980, 1-\beta^F$
$\rho^W, \theta^W, \iota^W$	Wage stickiness, bargaining power, inflation anchoring	$0.56, 0.51, 0.67$
γ^{PQ}	Max price-quantity exploration	0.05
ζ^P, ζ^Q	Speed of adjustment: price, quantity	$0.75, 0.75$
ω	Intensity of choice	10
$\bar{g}$	Maximum skill growth rate	0.0005
$\mathcal{N}^B$	Number of banks	10
γ^B, ω^B	Capital adequacy ratio, risk weighting	$0.08, 1$
$\varrho^B, \rho^B, \iota^B$	Bank financial soundness, firm leverage, NPL share	$0.029/4, 0.017/4, 0.001/4$
θ^B	Loan repayment rate	0.0125
p^*, u^*, r^*	Monetary policy target: inflation, unemployment target, real rate	$0.02/4, 0.087, 1/\beta^C - 1$
λ^p, λ^u	Monetary policy weights: inflation, unemployment	$1.41, 0.11$
b^*, ψ^G	Fiscal policy target: debt-GDP, tax-subsidy ratio	$0.75, 0.094$
ρ^{CB}, ρ^G	Policy adjustment speed: monetary, fiscal	$0.850.007$
$\mathcal{Z}^C, \mathcal{Z}^E, \mathcal{Z}^K, \mathcal{Z}^N, \mathcal{Z}^B$	Max new partners in markets	$0.25, 4, 4, 10, 0.2$

Appendix D. Empirical validation

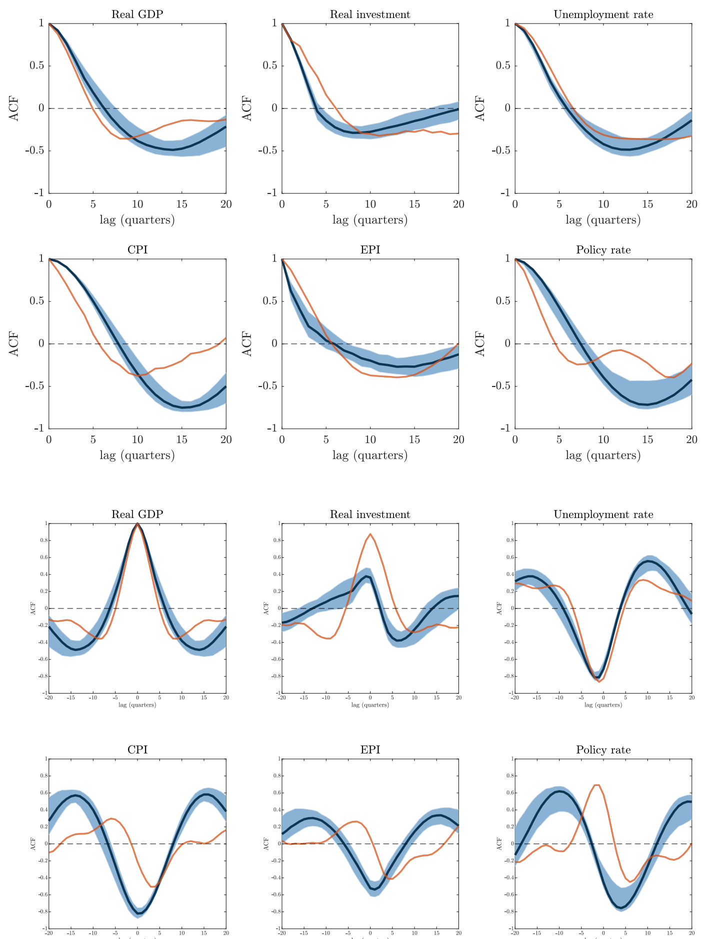

Figure D.9: Auto- and cross-correlation of key macroeconomic variables, de-trended with the HP filter. Simulated data show the mean and 95% CI from 250 MC simulations, while empirical data (orange) cover 1971Q1-2019Q4 from the ECB Area-Wide Model (AWM).

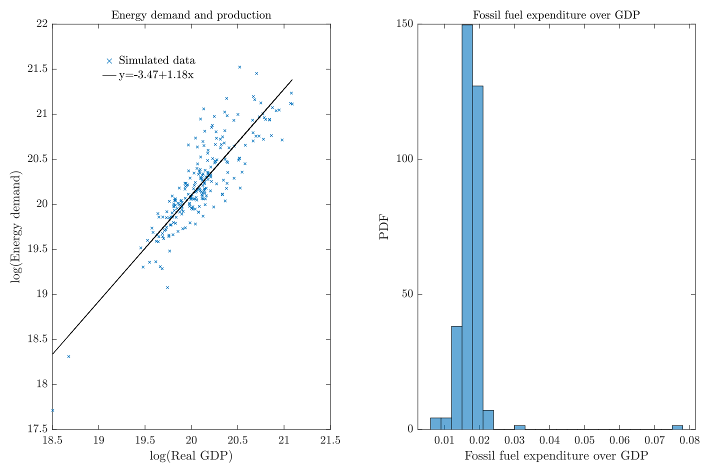

Figure D.10: Correlation between (log) energy demand and real GDP (left), and the share of fossil fuels in GDP (right) at the end of the simulation from 250 MC simulations.

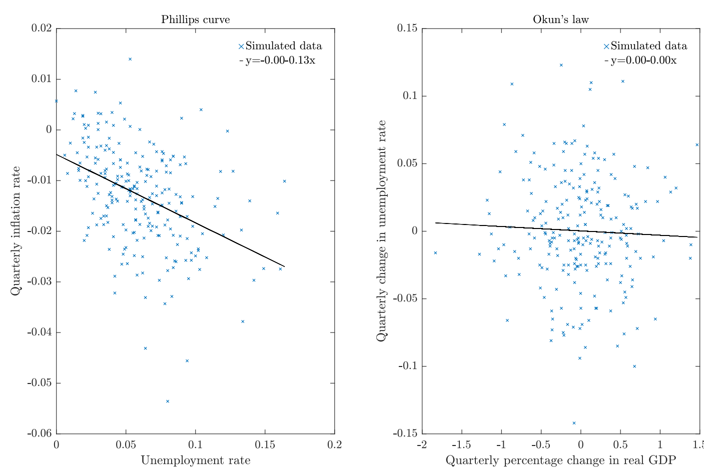

Figure D.11: Pillips curve (left), and Okun's law (right) at the end of the simulation from 250 MC simulations.

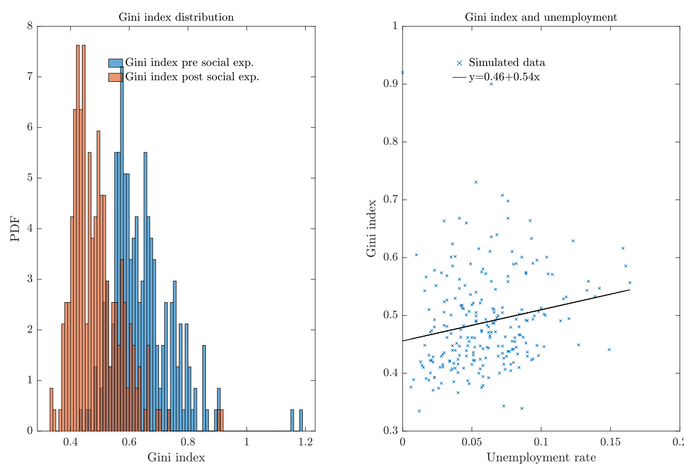

Figure D.12: Pre- and post-redistribution Gini index (left), and its correlation with the unemployment rate (right) at the end of 250 MC simulations.

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