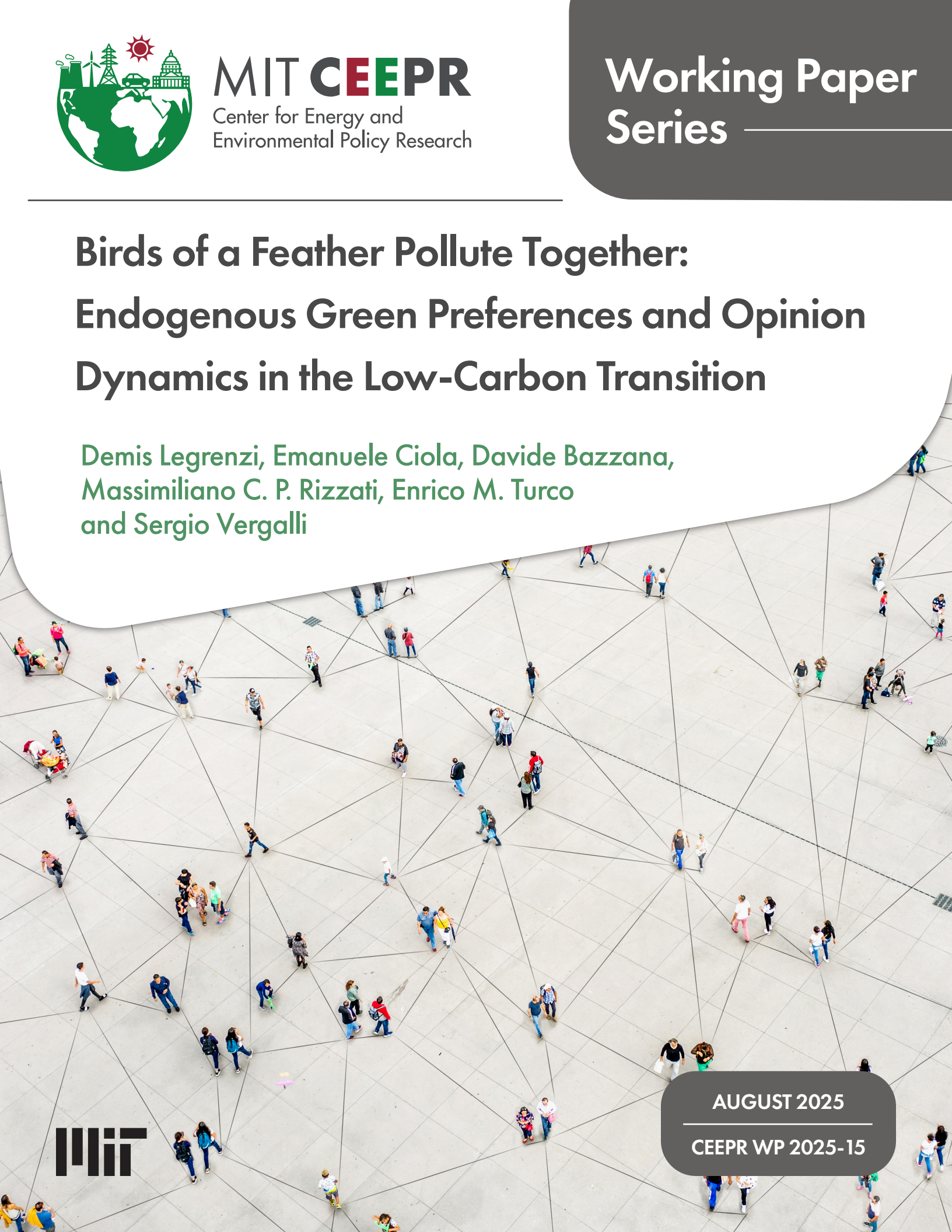
MIT CEEPR
Center for Energy and Environmental Policy Research

Working Paper Series

Birds of a Feather Pollute Together: Endogenous Green Preferences and Opinion Dynamics in the Low-Carbon Transition

Demis Legrenzi, Emanuele Ciola, Davide Bazzana, Massimiliano C. P. Rizzati, Enrico M. Turco and Sergio Vergalli



AUGUST 2025

CEEPR WP 2025-15

Working Paper Series.

Since 1977, the Center for Energy and Environmental Policy Research (CEEPR) has been a focal point for research on energy and environmental policy at MIT. CEEPR promotes rigorous, objective research for improved decision making in government and the private sector, and secures the relevance of its work through close cooperation with industry partners from around the globe. Drawing on the unparalleled resources available at MIT, affiliated faculty and research staff as well as international research associates contribute to the empirical study of a wide range of policy issues related to energy supply, energy demand, and the environment.

An important dissemination channel for these research efforts is the MIT CEEPR Working Paper series. CEEPR releases Working Papers written by researchers from MIT and other academic institutions in order to enable timely consideration and reaction to energy and environmental policy research, but does not conduct a selection process or peer review prior to posting. CEEPR's posting of a Working Paper, therefore, does not constitute an endorsement of the accuracy or merit of the Working Paper. If you have questions about a particular Working Paper, please contact the authors or their home institutions.

Birds of a Feather Pollute Together: Endogenous Green Preferences and Opinion Dynamics in the Low-Carbon Transition

Demis Legrenzi[1,2,3], Emanuele Ciola[1,2], Davide Bazzana[1,2], Massimiliano Carlo Pietro Rizzati[1,2], Enrico Turco[1,4], and Sergio Vergalli[1,2]

[1]Fondazione Eni Enrico Mattei, Italy
[2]Department of Economics and Management, University of Brescia, Italy
[3]CEEPR, Massachusetts Institute of Technology, USA
[4]The Complexity Lab in Economics, Department of Economics and Finance, Catholic University of Milan, Italy

July 30, 2025

Abstract

This work analyzes the effects and feedback of endogenously evolving consumer green preferences and social influence on firms' investment decisions to reduce CO2 emissions. While the existing literature mostly treats the issues of pro-environmental purchase decisions and decarbonization separately, we adopt a cohesive framework to bridge the gap between consumption and production. Using the Multi-Agent model for Transition Risks (MATRIX), a stock-flow-consistent, agent-based, integrated-assessment model, we endogenize green preferences for consumption goods and extend them with an opinion dynamics module. We find that endogenous green preferences can accelerate the green transition by complementing carbon taxation. However, imitation among households produces non-trivial effects: without large-scale, coordinated abatement efforts by firms, sporadic investments fail to generate sufficient momentum to shift preferences toward greener products. Consequently, while individual-level actions may favor full CO2 emissions reduction, anti-environmental social norms dominate, hindering the green transition.

Keywords: Agent-based model; Green preferences; Opinion dynamics; Carbon abatement; Carbon tax.

JEL Classification: C63; D9; Q5; Q58.

1 Introduction

The transition towards greener and more environmentally sustainable business models has gained significant traction among companies in recent decades. Green accounting and communication of firms' environmental values have emerged as critical competitive strategies in the consumer goods market (Ghosh, 2019; Mukonza and Swarts, 2019). At the same time, increased environmental awareness, effective marketing campaigns, and improved education on environmental issues have gradually influenced consumers to pay greater attention to the products they purchase and the social implications of their choices (Bedard and Tolmie, 2018; Joshi et al., 2021). In this sense, when a substantial portion of consumers is committed to sustainability, a new consumption paradigm may emerge, encouraging firms to adopt greener practices. However, the extent to which peer effects and opinion diffusion affect green investments (e.g., emissions abatement) remains a topic of ongoing debate.

Green preferences and their implications have been extensively studied across various disciplines (see Peattie, 2010, for a review). While much of this research focuses on the role of attitudinal factors in shaping Willingness To Pay (WTP) for sustainable products (Rowlands et al., 2003; Ek, 2005; Kotchen and Moore, 2007; Diaz-Rainey and Ashton, 2010), some analyses explore how social influence affects consumers purchasing decisions (Frank, 1985; Sangroya and Nayak, 2017). A novel direction in the field is represented by the combination of Integrated Assessment Modeling (IAM) with opinion dynamics (Lackner et al., 2025) to provide insights for policy support. However, these works overlook the interplay between consumers and firms, focusing on only one market side at a time and potentially missing the more general dynamics that may emerge from their interaction.

Our study addresses this gap in the literature by investigating how social influence and endogenous green preferences for consumption goods interact with firms' investment decisions in reducing aggregate emissions. Specifically, we explore whether the uncoordinated actions of consumers and firms can (endogenously) reinforce each other, fostering a virtuous cycle toward lower carbon emissions. At the same time, since green consumption preferences represent just one side of the spectrum, we allow households to develop anti-environmental preferences; i.e., we consider the possibility of lock-in effects that may emerge during this process and avoid the transition to a low-carbon economy. In fact, in our "integrative framework" (see Jackson et al., 2005), individual preferences can be swayed or reinforced with social interaction. Lastly, we complete our analysis by examining the potential interaction of such behavior with carbon taxation, a standard climate policy tool.

We address these questions by employing the *Multi-Agent model for Transition Risks* (MATRIX) calibrated on the Euro Area (EA) economy (Turco et al., 2023; Bazzana et al., 2024). The MATRIX is a stock-flow consistent (SFC), agent-based integrated assessment model (AB-IAM). It is a macroeconomic model with multiple sectors and populated by heterogeneous households, banks, and firms producing energy, consumption goods, and

capital goods.[1]

In this new version, we incorporate endogenous green preferences in the consumption goods market to investigate their interaction with firms' abatement decisions and the government's climate targets. In particular, pro-environmental preferences can impact the profits of firms producing consumption goods, favoring less polluting ones and guiding the abatement decisions of competitors via imitation. Further, by introducing an opinion dynamics module into the preference formation mechanism, we produce a range of results that carry significant implications for policymakers. Unlike the representative agent framework, our model can keep track of the income of each household over time, allowing us to identify similar consumers, model their social interactions, and improve the realism of our results.

Our contribution is twofold. Firstly, we broaden the green preferences literature (Busato et al., 2022a; Perusset, 2025), further supporting the positive influence of environmentally conscious consumption choices on the green transition by endogenizing preferences formation. In doing this, we develop an integrative pro-environmental behavior model (Jackson et al., 2005; Rhodes et al., 2017). Secondly, we contribute to the growing literature on Agent-Based Modeling (ABM) in the context of opinion dynamics and the green transition (Zeng et al., 2020; Lipari et al., 2024; Lackner et al., 2025). In particular, we bridge the gap between consumption and production. Households' pro-environmental preferences affect firms' investments, which in turn affect the government's climate targets and the intensity of climate policy, in a multi-layered feedback loop. Here we find a counterintuitive but significant result for policymakers: peer effects may not necessarily aid the green transition. Indeed, when agents observe anti-environmental attitudes in their network, collective opinion can outweigh individual green preferences. In this scenario, achieving a substantial shift toward pro-environmental attitudes requires extraordinary coordination among agents to align the preferences of the entire network, thereby diminishing the likelihood of a successful transition. However, policymakers can still leverage this dynamic by pushing abatement investments in the short term. Such early interventions may initiate a virtuous cycle, reducing the need for carbon taxation in the long term.

The remainder of the article is structured as follows. Section 2 reviews the reference literature, further explaining how this study extends existing results. Section 3 describes the extensions proposed for the MATRIX model. Section 4 presents the scenarios and policy experiments, whereas Section 5 shows the simulation results. Finally, Section 6 provides concluding remarks, main limitations, and future extensions of the analysis.

[1]The model has been employed in the past to study macroeconomic and financial risks of the energy transition (Bazzana et al., 2024), the economic and distributional impact of energy shocks and related stabilization policies (Ciola et al., 2023; Turco et al., 2023), as well as the potential of pro-environmental attitudes in fostering the green transition (Rizzati et al., 2025).

2 Literature

Several studies tackle pro-environmental opinion dynamics and their influence on technological change (Zeng et al., 2020) or policy support (Maestre-Andrés et al., 2019; Douenne and Fabre, 2020, 2022; Konc et al., 2022; Sælen and Aasen, 2023).

Lipari et al. (2024) explore the interaction between social and political dynamics, as well as their effects on support for climate policy. Their results show how peer effects positively affect pro-environmental behavior, regardless of the type of policy applied. Zeng et al. (2020) develop an ABM featuring a relative agreement opinion dynamics model to study the co-evolution of green technology diffusion and consumers' green attitudes. They find that increasing pro-environmental attitudes among consumers is greatly beneficial to the diffusion of green technology. Moreover, they observe the emergence of anti-environmental consumers during the evolution of attitudes.

Conversely, the integration of opinion dynamics within macro-ABMs is a relatively novel application, especially in the context of the green transition. Lackner et al. (2025) extends the EU-calibrated DSK model to explore the co-evolution of mitigation policies and public support. Their framework considers macroeconomic transition costs, climate change perception, lobbying, and social influence in shaping opinion dynamics in relation to several mitigation policies. They find that social influence is the main driver of opinion change, by greatly amplifying the impact of personal experiences. However, the link between the opinion dynamics module and the DSK is one-way, meaning that public support does not affect policy or technological development.

Accordingly, we contribute to this literature by connecting an opinion dynamics module to endogenously evolving consumption preferences in an ABM. In particular, we extend the MATRIX model to include an integrative framework describing the evolution of pro-environmental behavior.[2] This setting allows consumers' preferences to influence firms' green investment decisions by affecting their profitability and vice-versa. To develop such an extension of the MATRIX model emulating the behavior of environmentally-conscious consumers, we endow households with new features and heuristics grounded in empirical evidence.

Demographic and economic factors play a significant role in shaping consumer evaluations of green products in the market. While the specifics of these factors may vary across countries with different income levels, demographic structures, and wealth distributions, studies focusing on advanced economies consistently find a positive correlation between income and WTP for greener energy products (Zarnikau, 2003; Rowlands et al., 2003; Ek, 2005; Kotchen and Moore, 2007; Diaz-Rainey and Ashton, 2010), even though this relationship is not always linear (Yu et al., 2014). Perceived social approval (Sangroya and Nayak, 2017) and peer pressure further influence consumer behavior. Concerning peer effects, social status and material wealth relative to one's peers appear to be fundamental drivers of purchasing decisions (Frank, 1985).

[2] According to the categories developed by Jackson et al. (2005), integrative frameworks treat green preferences as a function of motivations considered "internal" to the agent (i.e., beliefs and values) and "external" (i.e., economic constraints and institutional factors).

Christakis and Fowler (2012) give three possible motivations for clustering of individuals within social networks: *homophily*, where individuals tend to associate with others with similar characteristics; *omitted variables*, where individuals and their neighbors could experience unobserved simultaneous influences, causing their attributes to covary; and *induction*, where individuals could be influenced by their neighbors. Induction and homophily can be easily integrated into an agent-based framework. In this sense, the MATRIX model can keep track of the income of each household over time, allowing us to identify similar consumers and model their social interaction.

In a broader setting, Dickinson et al. (2013) find that violating established social norms can have negative reputational consequences while being included in cooperative actions and observing cooperation among peers stimulates further cooperation. However, pro-social behavior is not exclusively observed when reputational punishments or rewards are active. Neuroscientific studies show that making equitable decisions and fighting inequality on our peer's behalf can engage neural structures acting as intrinsic rewards and giving us material pleasure (Harbaugh et al., 2007; Steger et al., 2008; Waytz et al., 2012). Still, Dimant (2019) finds a disparity between the effects of pro-social and anti-social behavior in terms of contagiousness, with anti-social behavior being the dominant force between the two and benefiting the most from social proximity. Further, anti-social subjects are more susceptible to contagion from other anti-social individuals. These studies provide grounds for the inclusion of anti-environmental preferences in our framework, since they may have a significant impact on abatement investments.

The opinion dynamics literature offers a variety of modeling approaches to opinion convergence within a network (Degroot, 1974; DeMarzo et al., 2003; Jackson and Yariv, 2007; Mueller-Frank and Neri, 2013; Banerjee et al., 2021). Mastroeni et al. (2019) survey the literature on ABMs for opinion formation, identifying their main features. Most studies employ a continuous (or bounded) opinion domain, a bilateral interaction direction (i.e., influence between two agents goes both ways), and they do not adopt a utility function to update their opinion. Concerning the latter, we adopt a hybrid approach to utility, in which internal preferences are the product of utility maximization, whereas the social component operates outside of it. In a way, we assume that consumers try to be rational about their purchase decisions but are still affected by the heuristics governing peer influence. Concerning network structure, the literature is evenly distributed among those that apply pairwise (i.e., couples of agents influence each other), any-to-any (i.e., all agents are influenced by all agents), and closest neighbor interactions (i.e., agents are influenced by a group of agents). In our model, we test both the any-to-any (see for instance: Degroot, 1974; Friedkin and Johnsen, 1990) and closest neighbor (among them: Hegselmann and Krause, 2002; Altafini, 2013) instances in a dynamic network, finding they yield comparable results. We depart from most literature by assuming symmetry in agent interactions, and all agents have the same weight when it comes to influencing a neighbor's opinion (Deffuant et al., 2000; Weisbuch et al., 2002).

Regardless of increasing support for environmentally friendly consumption choices, empirical evidence shows a gap between WTP (or purchase intentions) and actual behavior (Peattie, 2010; Wei et al., 2017; Nguyen et al., 2018), also known as the value-action

gap. While income promotes purchase intentions, its impact on actual purchase behavior can be much weaker. The gap's size is found to vary with costs associated to pro-environmental behaviors (Binder and Blankenberg, 2017) and consumers' dicretionary time (Chai et al., 2015). Social imitation of visible mitigation practices may reduce the gap (Babutsidze and Chai, 2018). In our model, green preferences apply to nondurable consumption goods alone. We assume that consumption choices can be observed by neighbors and we account for the gap by reducing the probability of consumers revising their green preferences (although we perform sensitivity analysis on it).

Finally, Aghion et al. (2023) show how consumers' environmental concerns can shape the direction of innovation. Firms seek to improve green technologies when they witness more environmentally motivated customers, even when an individual does not witness any direct improvement that can be tracked back to their own actions. Overall, they provide support for models in which the contribution of both pro-environmental attitudes and competition can shape a path that fosters cleaner technologies. Furthermore, they show that environmentally motivated individuals are willing to incur extra costs to act virtuously, regardless of positive feedback. In our model, green consumers can redirect purchases towards greener firms and away from more polluting firms. This may lead to a winning green business model prompting other firms to invest in abatement, triggering a virtuous cycle.

3 Model

The MATRIX (Ciola et al., 2023; Turco et al., 2023; Bazzana et al., 2024; Rizzati et al., 2025) is a stock-flow consistent, agent-based, integrated assessment model. It comprises multiple interconnected sectors, each populated by heterogeneous agents interacting in decentralized markets. These sectors include households ($h = 1, \ldots, \mathcal{N}^H$), firms ($f = 1, \ldots, \mathcal{N}^F$) operating in various industries (energy services – E, capital – K, and consumption goods – C), banks ($b = 1, \ldots, \mathcal{N}^B$), and public institutions, including a government and a central bank.

Households consist of workers and entrepreneurs, with the former earning wages and the latter receiving dividends from firms. Households allocate their income to consumption and bank deposits (i.e., personal savings). Firms produce goods using labor and other inputs through a Constant Elasticity of Substitution (CES) production function.

Energy firms (E-firms) require labor, capital, and fossil fuels to produce energy services. The output of E-firms serves as an input for capital (K) and consumption (C) goods firms. Similarly, K-firms produce intermediate capital goods necessary for production across all sectors, while C-firms sell final goods to households. Banks provide credit to firms, earn interest on loans, and gather deposits. The government collects taxes on profits (and, in specific scenarios, emissions) while funding social transfers. The central bank sets the policy rate based on inflation, unemployment, and growth targets. Lastly, an external representative agent akin to a foreign monopolist infinitely supplies fossil fuels to producing firms at a given price. The consumption of fossil fuels generates CO2-equivalent emissions, which contribute to their stock accumulation, driving increases in

global mean temperature.

In this paper, we extend the MATRIX model calibrated on the EA economy to focus on consumer behavior, specifically how consumption habits evolve endogenously in response to producers' abatement efforts and peers' imitation pressure. To model this, we modify the decentralized matching protocol through which consumers select sellers in the consumption goods market. In the original version, households have limited information-seeking capabilities and observe a constrained set of potential sellers, then ranked based on the utility derived from the goods they supply (i.e., on the consumed quantity). Following the approach of Yang et al. (2022), we adjust the utility function of each household to incorporate heterogeneous and endogenous green preferences, as well as social dynamics. Household networks are then mapped based on similarity in real disposable income, allowing for the simulation of peer influence on consumption choices.

In the following section, we provide a detailed explanation of the modifications made to the extended MATRIX model, while the foundational workings of the model are outlined in the Appendix (see Appendices A.1 through A.7). The parameter values, descriptions, and sources are presented in Appendices A.8 and A.9.

3.1 Abatement technology

Green investments are similar to Bazzana et al. (2024), where they take the form of generic perishable Abatement Technology (AbT) provided by an external monopolist with infinitely elastic supply.[3]

The AbT leads to a percentage reduction in the emission intensity of each firm f, $\hat{e}_{f,t}$, through a discrete process characterized by a maximum number J^{AbT} of abatement steps, each diminishing the emission intensity by δ^{AbT} percentage points. Therefore, the actual percentage reduction in emissions by each firm depends on the chosen step $J^{AbT}_{f,t}$, such that $\hat{e}_{f,t} = J^{AbT}_{f,t} \cdot \delta^{AbT}$. The size of the investment (i.e., the chosen abatement step) is determined through a *social learning* process by which firms adopt the abatement strategies of more profitable competitors selected randomly from a subset of all companies (i.e., via imitation). This mechanism ensures that, even in the absence of carbon taxation, firms may still pursue abatement investments driven by green preferences, provided those result in higher profitability for companies engaging in abatement efforts. In the residual case, if no more profitable competitor is identified, firms explore the surroundings of their current strategy at random.

In line with existing evidence, the AbT comes with increasing Marginal Abatement Costs (MAC). Specifically, the abatement cost $AC_{f,t}$ is a function of the reduction in the emission intensity $\hat{e}_{f,t}$ and the firm's nominal expenditure on fossil fuels $P^O_t O_{f,t}$ (see Bazzana et al., 2024; Rizzati et al., 2025), namely:

$$AC_{f,t} = AC\left(\hat{e}_{f,t}\right) P^O_t O_{f,t} = \sum_{j=0}^{J^{AbT}_{f,t}} \delta^{AbT} MAC\left(j \cdot \delta^{AbT}\right) P^O_t O_{f,t}, \tag{1}$$

[3]To preserve stock-flow consistency as in previous versions of the model, both the fossil rents and the abatement costs paid to external monopolists are redistributed to households according to their wealth.

where $O_{f,t}$ is fossil fuel consumption, P_t^O the price of fossil fuel, and $J_{f,t}^{AbT}$ is the selected number of abatement steps chosen by the firm.

Lastly, since implementing new AbT is often a lengthy process (or at least unrealistic on a quarterly basis), we assume firms update their abatement strategy with a certain probability θ^{AbT}.

3.2 Consumption budget

Depending on their type, the nominal income for each household h at time t is given by:

$$Y_{h,t} = \begin{cases} W_t N_{W,t} & \text{for workers,} \\ DIV_{f,t} - REC_{f,t} & \text{for entrepreneurs,} \\ DIV_{b,t} - REC_{b,t} & \text{for bankers,} \end{cases} \tag{2}$$

where wages, W_t, multiplied by the actual units of labor, $N_{W,t}$, represent the sole source of income for workers, while entrepreneurs and bankers earn dividends and face recapitalization costs for defaulted firms or banks they own ($DIV_{s,t}$ and $REC_{s,t}$, with $s = \{f, b\}$, respectively). Accordingly, the net income, $Y_{h,t}^{net}$, is a function of nominal income, $Y_{h,t}$, the tax rate, τ_t^{tax}, and social transfers, $TRA_{h,t}$ (if the household is eligible), as expressed by the equation:

$$Y_{h,t}^{net} = \left(1 - \tau_t^{tax}\right) Y_{h,t} + TRA_{h,t}. \tag{3}$$

Following Ciola et al. (2023), the real permanent income is determined as follows:

$$\bar{Y}_{h,t} = \left(1 - \beta^C\right) \frac{Y_{h,t}^{net}}{\mathbb{E}_{h,t}\left[P_{c,t}\right]} + \beta^C \bar{Y}_{h,t-1}, \tag{4}$$

where $\beta^C \in (0, 1)$ is the household's discount rate, $\bar{Y}_{h,t-1}$ is past real permanent income, and $\mathbb{E}_{h,t}\left[P_{c,t}\right]$ is the expected price index on consumption goods.[4] Thus, the household's consumption budget is equal to:

$$H_{h,t}^d = \bar{Y}_{h,t} + \chi D_{h,t}, \tag{5}$$

with $D_{h,t}$ being the household's deposits, and $\chi = 1 - \beta^C$ the propensity to consume out of accumulated financial wealth.

As a consequence, the law of motion of deposits depends on their past stock $D_{h,t-1}$, net income, and actual consumption expenditure $H_{h,t}$:

$$D_{h,t} = D_{h,t-1} + Y_{h,t}^{net} - H_{h,t}, \tag{6}$$

with $0 \leq H_{h,t} \leq H_{h,t}^d$ derived from the matching on the consumption good market. Indeed, consumers are forced into involuntary savings if companies do not supply enough goods.

[4]Prices are expected since households (and firms) compute consumption budgets (input demands) before the respective markets open. Their value consists of the price observed in the previous period plus the expected inflation rate, the latter being equal to the growth in firms' production costs.

3.3 Matching protocol and green preferences

Demand is allocated through a recursive decentralized matching protocol, adapted from the literature on dynamic network formation (Berardi and Tedeschi, 2017; Ciola et al., 2023).

In every period, households interact with their previous suppliers and $\mathcal{Z}_h$ new partners. Among them, the selected partner is the seller whose offer maximizes the household utility (Rizzati et al., 2025):

$$U_{h,t|f} = \log\left(X_{h,t|f}\right) - \eta_{h,t}\left(1 - \hat{e}_{h,t|f}\right), \tag{7}$$

which depends on the consumed quantity $X_{h,t|f}$, equal to the ratio of household h consumption budget $H^d_{h,t}$ to firm f price $P_{f,t}$, i.e., $X_{h,t|f} = H^d_{h,t}/P_{f,t}$, and the green preferences component. The latter is represented by the endogenous factor $\eta_{h,t}$, which captures the semi-elasticity between the quantity purchased $X_{h,t|f}$ and the percentage reduction in the observed emission intensity of the seller, i.e., $\hat{e}_{h,t|f} = \hat{e}_{f,t}$. In other words, $\eta_{h,t}$ is a proxy for the intensity of the household's green preferences, with no restrictions on its sign.

Switching to a product (supplier) with a lower emission intensity increases the value of $\hat{e}_{h,t|f}$, thereby reducing the loss of utility connected to the consumption of polluting products. The higher the value of $\eta_{h,t}$, the stronger the consumer's green preferences, and the higher the reduction in the utility loss.[5] However, when $\eta_{h,t}$ turns negative, households perceive an increase in utility as the products they consume become more pollutant, indicating the development of brown preferences. In the case $\eta_{h,t} = 0$, consumers' choices are unaffected by emissions and are solely guided by prices and quantities.[6]

To explain the green preferences formation mechanism, namely, how the value of $\eta_{h,t}$ varies over time, we further distinguish between a household's green purchase behavior (captured by the green preferences, $\eta_{h,t}$) and its green purchase intention. Green purchase intention $\eta^*_{h,t}$ varies according to two components: one is *internal*, $\hat{\eta}_{h,t}$, and the other is *social* (or imitative), $\tilde{\eta}_{h,t}$, namely:

$$\eta^*_{h,t} = \phi^{GP}\hat{\eta}_{h,t} + \left(1 - \phi^{GP}\right)\tilde{\eta}_{h,t}, \tag{8}$$

where $0 \leq \phi^{GP} \leq 1$ determines the relative weight of the internal and social components in the formation of green attitudes.

Each household determines the internal component individually, gradually modifying its value over time following a partial adjustment mechanism, whose direction depends on the sign of the green preference variation $\mathrm{d}\hat{\eta}_{h,t}$. In particular, movements along the iso utility curve (7) imply the following total differential:

$$\mathrm{d}U_{h,t|f} = \frac{1}{X_{h,t-1|f}}\mathrm{d}X_{h,t|f} - \left(1 - \hat{e}_{h,t-1|f}\right)\mathrm{d}\eta_{h,t} + \eta_{h,t-1}\mathrm{d}\hat{e}_{h,t|f} = 0. \tag{9}$$

[5] While some of the literature (Chan, 2019; Busato et al., 2022b) directly incorporates negative climate feedback in the form of disutility, it is plausible that a degree of human acclimatization to worsening environmental conditions could mitigate this effect (Kahneman and Tversky, 1979). Therefore, we exclude a macro-scale climate feedback component in the household's decision process.

[6] Accordingly, we initialize all households to this value in every simulation.

By rearranging the terms, we obtain:

$$\mathrm{d}\hat{\eta}_{h,t} \approx \frac{1}{1-\hat{e}_{h,t-1|f}} \left(\eta_{h,t-1} \Delta \hat{e}_{h,t|f} + \frac{\Delta X_{h,t|f}}{X_{h,t-1|f}} \right). \tag{10}$$

In other words, assuming constant utility over time, green preferences increase with consumption growth $\Delta X_{h,t|f}/X_{h,t|f}$,[7] and perceived abatement efforts $\Delta \hat{e}_{h,t|f}$. It is important to note that, since sellers can change over time, the variation in the observed emission intensity does not necessarily reflect the overall economy's emission intensity.

Accordingly, the internal component varies endogenously according to the rule:

$$\hat{\eta}_{h,t} = \begin{cases} \hat{\eta}_{h,t-1} + \nu^{GP} & \text{if } \mathrm{d}\hat{\eta}_{h,t} > 0, \\ \hat{\eta}_{h,t-1} - \nu^{GP} & \text{otherwise,} \end{cases} \tag{11}$$

where ν^{GP} is a fixed step determining the adjustment speed of internal green preferences. Therefore, in the short term, households not only select the seller providing the highest benefit but also internalize the green attribute of a product by modifying their preferences such that their utility remains unchanged. By doing that, they continuously adapt their preferences based on the limited information from their personal experiences, potentially leading to a self-reinforcing process.

Concerning the social component,[8] the factor $\tilde{\eta}_{h,t}$ is the mean of the currently manifested green purchase intentions $\eta^*_{h,t}$ of a neighborhood K:

$$\tilde{\eta}_{h,t} = \frac{1}{|K|} \sum_{j \in K} \eta^*_{j,t}. \tag{12}$$

We define the neighborhood by applying a learning process based on the principles of homophily and induction (Christakis and Fowler, 2012). Specifically, we assume that the most similar households influence the opinion formation mechanism. Since the network is dynamic, the distance between two households is not determined by the minimum number of edges connecting them; rather, we redefine the network at each time step using a similarity metric. Therefore, the neighborhood (i.e., the households directly connected to a reference household) is updated by sampling from the $|K|$ highest scoring households based on the normalized similarity index $\varsigma_{i,j}$. For each (i,j) couple of households, $\varsigma_{i,j}$ is equal to:

$$\varsigma_{i,j} = 1 - \frac{(I_{i,j} - \min(I_{i,m}))}{(\max(I_{i,m}) - \min(I_{i,m}))}. \tag{13}$$

for $m \neq j \neq i$, where $I_{i,j} = |\bar{Y}_i - \bar{Y}_j|$ represents the difference in real permanent income between households i and j. In other words, we assume that households with similar wealth recognize each other and are more likely to interact.

[7] We adjust consumption growth for the exogenous growth factor ζ^{growth} (see Appendix).

[8] In the opinion dynamics, a relevant distinction in the literature concerns the use of continuous (e.g., Degroot, 1974) vs binary (e.g., Granovetter, 1978) opinion parameters. We adopt the continuous opinion approach, whereby the agent's preference is updated at each time step using the mean of other agents.

Finally, green purchase intentions $\eta^*_{h,t}$ can turn into green preferences (i.e., green purchase behavior) $\eta_{h,t}$ with a probability θ^{GP}:

$$\eta_{h,t} = \begin{cases} \eta^*_{h,t} & \text{with probability } \theta^{GP}, \\ \eta_{h,t-1} & \text{with probability } \left(1-\theta^{GP}\right). \end{cases} \tag{14}$$

This final step accounts for the intention-behavior gap by limiting the frequency with which a household revises its preferences, while still allowing preferences to influence other households' intentions through the social dynamics channel.

3.4 The government

The government can affect the stock of CO2 emissions and abatement decisions via fiscal policy by applying a carbon tax, which constitutes a source of revenue. More in detail, the public budget has two inflows and three outflows. It increases with income taxes (TAX_t) and carbon taxation (TAX^{CA}_t) if climate policy is active. Conversely, public expenditures have three destinations: interest payment on past public debt ($i^{CB}_t B_{t-1}$, where i^{CB}_t is the risk-free interest policy rate), transfers to low-income households (TRA_t), and bankrupt banks are (at least partly) recapitalized using public finances (EXP_t). Therefore, the law of motion of the government's budget (B_t) is:

$$B_t = \left(1+i^{CB}_{t-1}\right) B_{t-1} + TRA_t + EXP_t - TAX_t - TAX^{CA}_t. \tag{15}$$

The government is guided by a fiscal sustainability principle, with a target debt-to-GDP ratio (b^*). To keep track of fiscal sustainability, the debt-to-GDP ratio (b_t) is computed as:

$$b_{t+1} = \frac{1+i^{CB}_t}{1+g_t} b_t - f_{t+1}, \tag{16}$$

with $f_t \equiv \left(TAX_t - TRA_t - EXP_t\right)/GDP_t$ being the primary budget-to-GDP ratio, while g_t is the expected nominal growth rate of output at time t.

Thus, the government periodically adjusts the current level of b_t by applying the rule:

$$b_{t+1} = b_t + \rho^G \left(b^* - b_t\right), \tag{17}$$

where ρ^G captures the speed of adjustment of the debt-to-GDP ratio towards its target value b^*. By substituting equation (17) into equation (16) and rearranging the terms, it is possible to obtain the expected primary balance (f_{t+1}):

$$-f_{t+1} = \rho^G b^* + \left(1+\rho^G\right)\left[1 - \frac{1+i^{CB}_t}{\left(1+g_t\right)\left(1-\rho^G\right)}\right]. \tag{18}$$

The role of the government is to enforce a policy consistent with its fiscal sustainability objectives. In particular, the total social expenditures τ^{tra}_t (as a share of GDP) is governed by:

$$\tau^{tra}_t = \max\left[\psi^G, -f_{t+1}\right], \tag{19}$$

where ψ^G is a constant benchmark for social expenditure, and the tax rate setting follows the rule:

$$\tau_t^{tax} = \max\left[0, f_{t+1} + \tau_t^{tra}\right]. \tag{20}$$

In those scenarios where we introduce a carbon tax (following Bazzana et al., 2024), the government adopts a heuristic to endogenously vary the carbon tax rate to comply with a set emission target. The emissions target $\bar{E}^{CA}$ is obtained backward, by setting a target percentage reduction of emissions $\eta^{CA} \in [0,1]$ from a reference year t^*, such that $\bar{E}^{CA} = \left(1-\eta^{CA}\right) E_{t^*}$. Then, the government compares total emissions E_t to their target level $\bar{E}^{CA}$ and then applies a mechanism that increases or decreases the carbon tax rate by a fixed step ϵ^{CA} accordingly:

$$\tau_t^{CA} = \begin{cases} \tau_{t-1}^{CA} + \epsilon^{CA} & \text{if } E_t > \bar{E}^{CA}, \\ \tau_{t-1}^{CA} - \epsilon^{CA} & \text{otherwise.} \end{cases} \tag{21}$$

Finally, firms pay carbon taxes based on their emissions $E_{f,t}$:

$$TAX_t^{CA} = \tau_t^{CA^*} \sum_{f=1}^{\mathcal{N}^F} E_{f,t} = \tau_t^{CA^*} \sum_{f=1}^{\mathcal{N}^F} \varepsilon_{f,t} P_t^O O_{f,t}, \tag{22}$$

where $\varepsilon_{f,t} = e_{f,t}/e_{f^*,t^*}$ are the emission intensities for each firm respect to a baseline sector (f^*) and year (t^*), and $\tau_t^{CA^*} = \left(\tau_t^{CA} P_t^O\right)/e_{f^*,t^*}$ represents the implicit carbon tax set by the government.[9]

3.5 Emissions

Since our aim is to analyze how abatement investments and carbon taxation interact with endogenous green preferences and, in turn, how green preferences may affect mitigation, we apply the HECTOR carbon cycle (Hartin et al., 2015) to model the impact of the increase in the stock of CO2 emissions on global mean temperature (see Appendix A.5).[10]

More specifically, for what concerns GHG emissions, we compute global carbon dioxide emissions E_t^W as the sum of the endogenous emissions produced by the model (i.e., the Euro Area economy, E_t) and an exogenous component (E_t^{ROW}), namely:

$$E_t^W = E_t + E_t^{ROW}, \tag{23}$$

where E_t^{ROW} tracks emissions from the rest of the world. These are obtained as in Bazzana et al. (2024) by inferring their value from a Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT, see Dietz and Rosa, 1994, 1997) model estimated on global annual data.

[9] We adopt this notation since it allows subsequent conversion to real-world values.

[10] To keep the model as simple as possible, we exclude the direct feedback of climate damage with green preferences and emissions abatement decisions.

Conversely, endogenous emissions E_t are the sum of all GHGs released by individual firms, determined as the product of their specific emission intensities ($e_{f,t}$) and the amount of fossil fuels utilized ($O_{f,t}$):

$$E_t = \sum_{f=1}^{\mathcal{N}^F} e_{f,t} O_{f,t}. \tag{24}$$

4 Scenarios and policy experiments

Since our extension to the MATRIX model introduces four additional parameters (ν^{GP}, θ^{GP}, ϕ^{GP}, and $|K|$), we conduct a sensitivity analysis on their values to fully understand their impacts.

We perform four sets of experiments. The first two perform sensitivity analyses on the free parameters we introduce in the green preferences formation mechanism. The remaining experiments are dedicated to the interaction of green preferences with carbon taxation. Each scenario is tested against a Business-As-Usual (BAU) counterpart where abatement investments are inactive. For each experiment, we employ 250 Monte Carlo simulations. Each time step corresponds to a quarter, and each simulation is run for 1820 periods, where we discard the first 1500 as a *burn-in* phase to allow the model to reach its (statistical) steady state. The remaining 320 periods correspond to the desired $2020 - 2100$ timeframe. Lastly, we introduce green preferences, abatement investments, and carbon taxation in the year 2020. For each sensitivity experiment, we test three values: low, intermediate, and high.

We start by analyzing the internal component of green preferences (i.e., $\phi^{GP} = 1$) and we test a range of values for the adjustment speed parameter ν^{GP} and the switching probability (i.e., update frequency) of green preferences θ^{GP}. These scenarios (*GP Sensitivity*) are summarized in Table 1. The objective of this experiment is to observe the interaction of internal green preferences with abatement decisions and, as a consequence, emission intensities.

Then, we activate the social component and analyze several weights of the imitative process ϕ^{GP} for different sizes of the neighborhood $|K|$. In particular, when the household is myopic, we test the *closest-neighbor* approach and set $|K| = 2$. Conversely, when the household has a complete network and interacts with all other households (i.e., when $|K| = \mathcal{N}^H$), we test the *any-to-any* approach. These scenarios (*SN Sensitivity*) are reported in Table 2.

Finally, we introduce the carbon tax, in the purely internal case first and then by introducing social dynamics, testing for different adjustment speeds in the carbon tax setting mechanism (*Carbon Tax GP* in Table 3 and *Carbon Tax SN* in Table 4, respectively).

Table 1: Experiments on purely internal green preferences.

GP Sensitivity		ν^{GP}	θ^{GP}	ϕ^{GP}	$\lvert K\rvert$	ϵ^{CA}
Adjustment speed	*Slow*	0.005				
	Medium	0.010	1	1	–	–
	Fast	0.015				
Switching probability	*Rare*		0.25			
	Regular	0.010	0.50	1	–	–
	Frequent		0.75			

Table 2: Experiments including social component in preferences formation.

SN Sensitivity		ν^{GP}	θ^{GP}	ϕ^{GP}	$\lvert K\rvert$	ϵ^{CA}
Complete Network	*Low imit.*			0.75		
	Medium imit.	0.010	0.50	0.50	$\mathcal{N}^H - 1$	–
	High imit.			0.25		
Myopic Network	*Low imit.*			0.75		
	Medium imit.	0.010	0.50	0.50	2	–
	High imit.			0.25		

Table 3: Policy experiments with purely internal green preferences.

Carbon Tax GP		ν^{GP}	θ^{GP}	ϕ^{GP}	$\lvert K\rvert$	ϵ^{CA}
GP-CT	*Low (L)*					0.01
	Medium (M)	0.010	0.50	1	–	0.02
	High (H)					0.03

Table 4: Policy experiments including social component in preferences formation.

Carbon Tax SN		ν^{GP}	θ^{GP}	ϕ^{GP}	$\lvert K\rvert$	ϵ^{CA}
SN-CT	*Low (L)*					0.01
	Medium (M)	0.010	0.50	0.50	2	0.02
	High (H)					0.03

5 Results

5.1 Green preferences and abatement

In this section, we examine the results of the experiments testing the interaction of green preferences with abatement technology investments.

First, we deal with the experiments shown in Table 1, where only the internal component of green preferences is tested, performing a sensitivity analysis on the adjustment speed of green preferences and the switching probability.

Figure 1 displays the results for the *GP Sensitivity* experiment (i.e., concerning only internal green preferences) and shows the variation of $\bar{\eta}_t$, i.e., in the average value of $\eta_{h,t}$, weighted by the purchased quantities, from the BAU scenario. As the speed adjustment parameter ν^{GP} increases (*GP Slow*, *GP Medium*, and *GP Fast*), green preferences tend to increase more rapidly and peak sooner. The same applies to the switching probability θ^{GP} (*GP Rare*, *GP Regular*, and *GP Frequent*), and the magnitude of $\bar{\eta}_t$ reached in these scenarios is consistent with the empirical evidence found in the WTP literature (around 3% of disposable income for complete decarbonization, as in Viscusi and Zeckhauser, 2006; Roe et al., 2001; MacKerron et al., 2009).

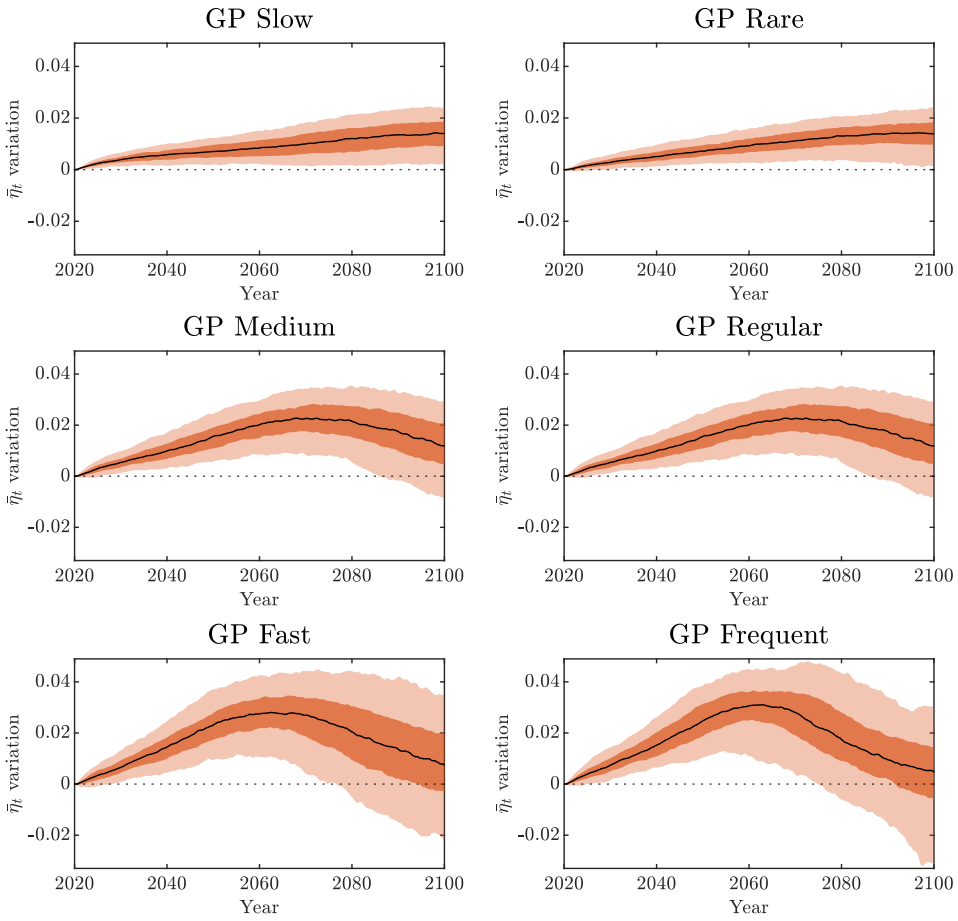


Figure 1: Weighted average green preferences ($\bar{\eta}_t$) variation in the *GP Sensitivity* experiment.

Note: The figures on the left show sensitivity results for the adjustment speed factor ν^{GP}, the figures on the right show sensitivity results for the switching probability θ^{GP}.

These results need to be interpreted together with the variation in emission intensities in the consumption good sector, shown in Figure 2. The shift of environmental preferences towards greener behavior seems to facilitate the investment in abatement technologies, determining the decline in emission intensities in the consumption goods sector. Investing in abatement becomes a profitable strategy for firms, that further benefit from showing consumers they are becoming more environmentally-friendly. As in Zeng et al. (2020), the improvement in the households' pro-environmental stance prominently benefits the diffusion of green technology. The decline in emission intensity is sharper when the adjustment speed or the update frequency of green preferences increases, leading to an anticipated achievement of the emissions abatement goals. At that point, when

a significant reduction in emission intensity is reached, green preferences lose their drive. When all firms are green, households do not witness a significant reduction in observed emission intensities anymore and start revising their green preferences downwards.

Thus, internal green preferences alone seem to be able to guide the green transition by spurring abatement investments to attain significant environmental goals. Nevertheless, the gap between intention and behavior in green consumption (i.e., a low level of θ^{GP}), as well as frictions of similar nature like indecisiveness or slow decision-making (i.e., a low level of ν^{GP}), may play a non-negligible role in delaying the adoption of green technologies by many years. These results differ from the ones found by Rizzati et al. (2025), where the MATRIX model is extended to incorporate fixed pro-environmental attitudes. In that setting, an active policy is still necessary to achieve the government's emission reduction goals. If not, exceptionally high green preferences are required to achieve the net-zero emissions outcome.

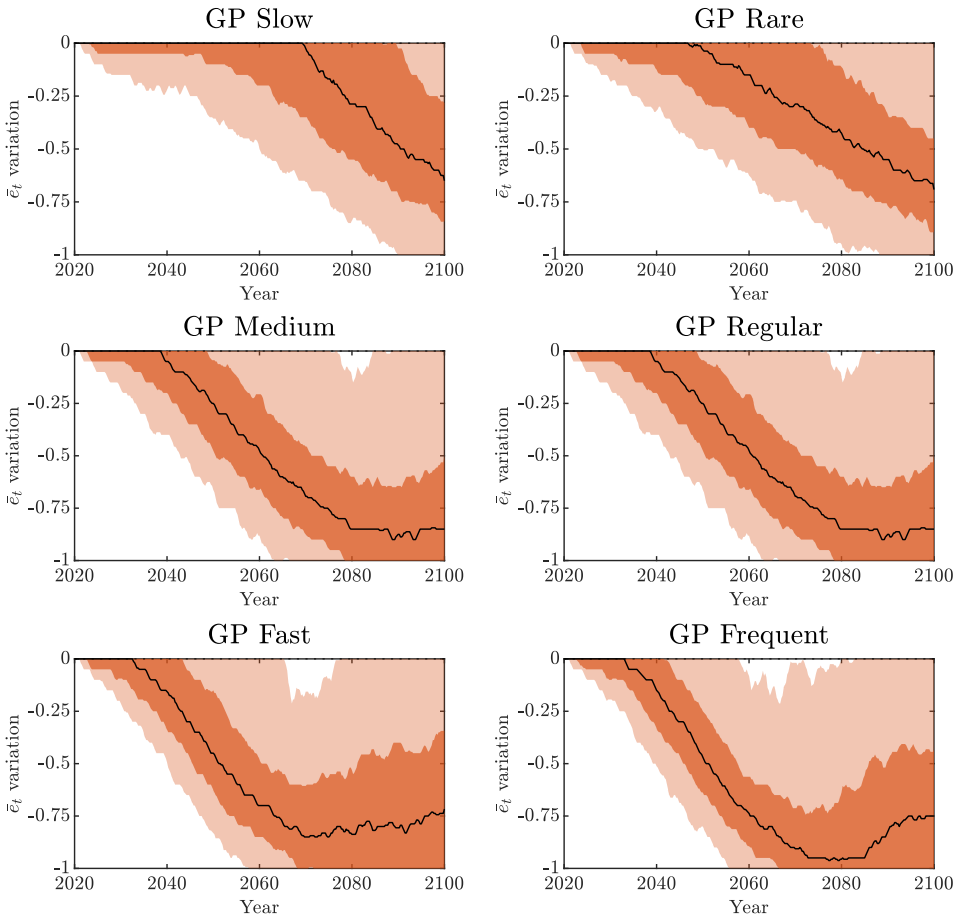


Figure 2: Mean Emission Intensity ($\bar{e}_t$) variation in the C-Sector in the *GP Sensitivity* experiment.

Note: The figures on the left show sensitivity results for the adjustment speed factor ν^{GP}, the figures on the right show sensitivity results for the switching probability θ^{GP}.

Results change significantly when we introduce the social component in green preferences. Figure 3 represents their values after implementing a social dynamics on top of the *GP Regular* scenario (see Table 2). We test for the complete network ($|K| = \mathcal{N}^H - 1$) and the myopic case (with a restricted neighborhood $|K| = 2$) over different levels of ϕ^{GP} (i.e., the strength of the imitative component, such that with $\phi^{GP} = 1$ the scenario collapses to the *GP Regular* case).

Unlike what we observed with internal preferences, $\bar{\eta}_t$ shows a feeble reaction to the introduction of abatement investments in all cases. When we compare the complete network to the myopic alternative, we do not notice substantial changes in the development of green preferences for the same level of ϕ^{GP}. For higher levels of ϕ^{GP} (less imitation),

both cases display an increase in variance (notice the width of the 90% confidence interval), showing that the imitative process allows to reach the same outcome as the purely internal case in only few instances.

Furter, for even high values of ϕ^{GP} (i.e., when the imitative process only accounts for one-fourth of the green preferences adjustment), Figure 3 hints at a generalized weakening of green preferences with a faint pressure towards the brown side of the spectrum. Even if the standard literature generally suggests that peer effects for a variety of consumption choices and behaviors support the green transition (see, among others, Perusset, 2025; Bigler and Janzen, 2023; Wang et al., 2021), our results are in line with Dimant (2019) and Tam and Chan (2023), which show how anti-social behavior may spread in the population, become the dominant force and negatively affect the green transition.

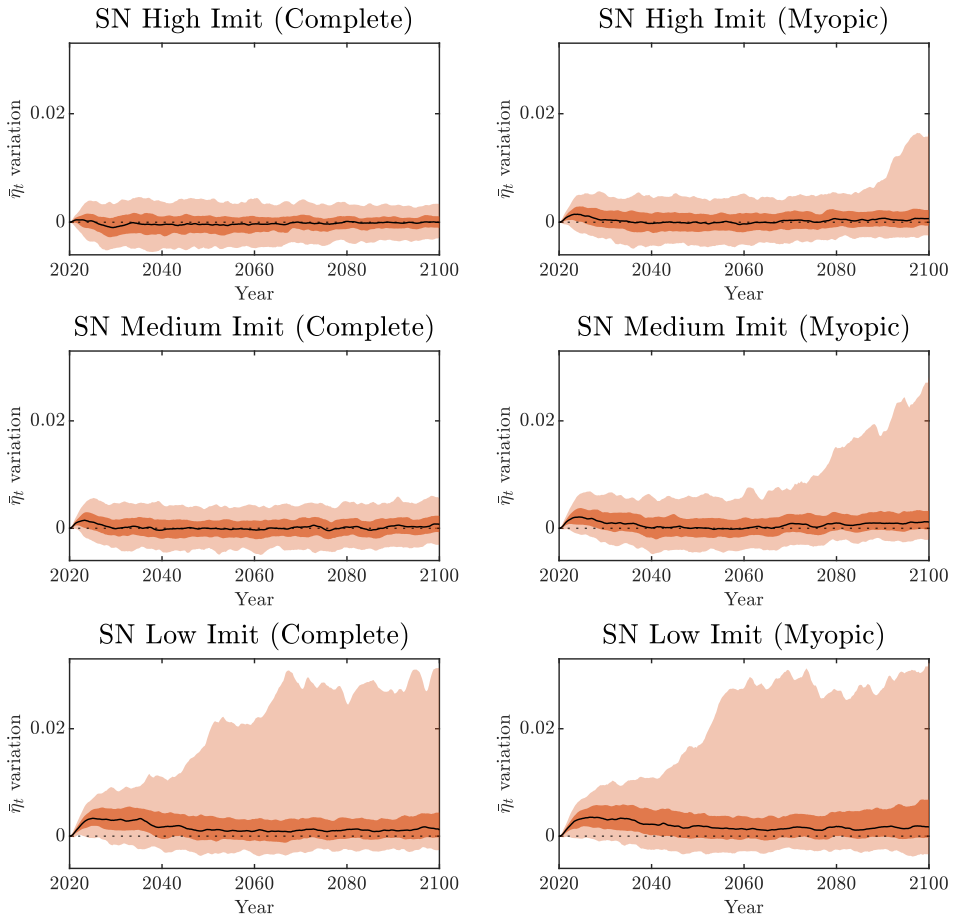


Figure 3: Weighted average green preferences ($\bar{\eta}_t$) variation in the *SN Sensitivity* experiment.

Note: The figures in the first column show sensitivity results for the imitation parameter ϕ^{GP}, with a complete network ($|K| = \mathcal{N}^H - 1$), and with a myopic network in the second column ($|K| = 2$).

Therefore, in the absence of a carbon tax, emission intensities (Figure 4) struggle to decline as abatement decisions rarely take place. These results are in line with Granovetter (1978), Chwe (2000), and Hsieh et al. (2023). Indeed, for collective action to arise, a critical mass of the population needs to display a high enough propensity for change. Since we make no assumptions on the initial distribution of green preferences (i.e., it is initialized as null for all agents), and since endogenous abatement investments do not directly account for the potential increase (or decrease) in sales coming from changes in preferences, such collective action rarely manifests in the system. In our dynamic

network, a small neighborhood offers slightly more opportunities to develop greener preferences in the long run compared to observing the whole population (even with a high imitation parameter). In some rare cases, small clusters of green households manage to slowly win over the entire population. Still, this is a marginal occurrence.

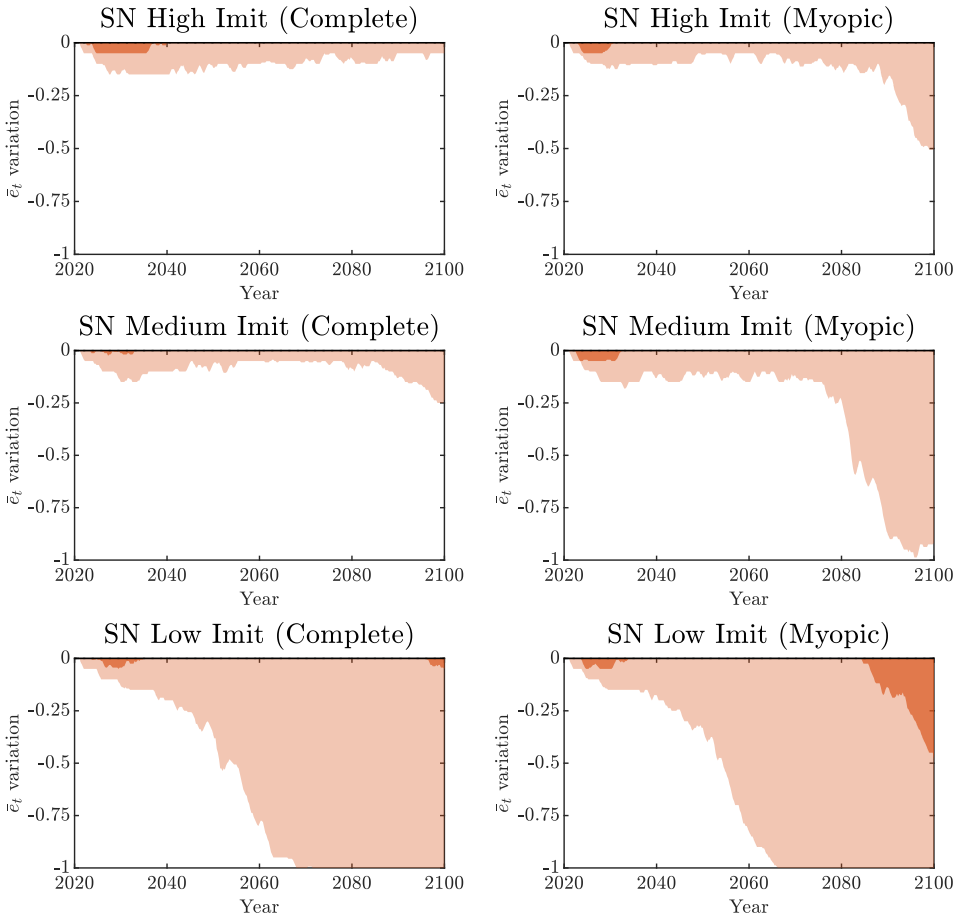


Figure 4: Mean Emission Intensity ($\bar{e}_t$) variation in the C-Sector in the *SN Sensitivity* experiment.

Note: The figures in the first column show sensitivity results for the imitation parameter ϕ^{GP}, with a complete network ($|K| = \mathcal{N}^H - 1$), and with a myopic network in the second column ($|K| = 2$).

A possible explanation for the severe reduction in the level of $\bar{\eta}_t$ witnessed after the introduction of the social component may depend on the need for a coordinated abatement effort by the firms. Without any external influence, companies do not have the incentive to engage in massive emission reductions in the short term, especially if consumers are

not yet willing to reward their efforts. Therefore, the sporadic adoption of early abatement investments by a single firm is severely diluted in the eyes of consumers when they consider their social network. Indeed, they weigh this information with that coming from their neighborhood, significantly limiting its extent and thus reducing their willingness to pay for green products. In other words, when consumers are somewhat aware (by exchanging information with their peers) of a more general state of the economy's abatement progress, they need to witness significantly higher and coordinated investments to be swayed to the green cause. In this situation, the virtuous cycle cannot begin without a strong and manifest commitment from the producers. The analysis reported in Appendix A.6 supports this interpretation.

5.2 Carbon taxation

We conclude by exploring the interaction between green preferences, firms' abatement decisions, and carbon taxation. In particular, we assess varying speeds of the government adjustment speed of carbon tax rates (i.e., ϵ^{CA}, see experiments in Table 3 and Table 4).

Starting from internal green preferences, as shown in the left panes of Figure 5, a faster carbon tax adjustment parameter anticipates the occurrence of pro-environmental attitudes but also accelerates their decline once emission reduction objectives have been achieved (Figure 6, left panes). Indeed, while the carbon tax speeds up the decrease in emission intensity (Figure 6, left panes), it parallelly reduces consumers' income, thus generating two counterbalancing effects in green preference variation (10). In particular, once emissions reach the desired value, the government stops increasing the carbon tax (Figure 7, left panes), and firms avoid making additional investments. As a result, consumers start suffering the loss of income due to carbon taxation ($\Delta X_{h,t|f} < 0$) without benefitting from supplementary reductions in emissions ($\Delta \hat{e}_{h,t|f} = 0$), thus explaining the endogenous change in their preferences.

If we consider the analogous cases in the presence of social dynamics, we observe that the variation in $\bar{\eta}_t$ is still negligible compared to the case without abatement for all levels of ϵ^{CA} (Figure 5, left vs right panes). Further, as shown in Figure 6, the impact of carbon tax is delayed compared to the purely internal green preferences case. As a result, the government must continue the policy for a protracted period, thus reaching higher values of taxation (Figure 7).

Nevertheless, a faster adjustment in the carbon tax rate partially offsets the slowdown induced by social dynamics. Specifically, it anticipates large-scale abatement by as much as 30 years. Interestingly, higher responsiveness in the carbon tax policy (SN CTH) leads to a peak in the carbon tax rate towards the mid to end century (Figure 7). This peak, around 700 EUR per Ton of CO2, is significantly higher than the one reached in the case with internal green preferences alone (around 500 EUR per Ton of CO2 in the GP CTH). But just like in the other case, as soon as the abatement target is reached, the fiscal pressure is released. Nevertheless, the carbon tax level remains well above the GP-CTH case at the end of the century.

Overall, if we compare the *Carbon Tax GP* and the *Carbon Tax SN* sets of scenarios, we notice that purely internal endogenous green preferences can reduce the need for

government intervention by partially substituting the role of carbon taxation in guiding abatement decisions. However, they have a limited extent. Indeed, once emissions reach the desired value and firms stop making additional investments, consumers start suffering the loss of income due to taxation and change their behavior. In this sense, managing such a variation in preferences while keeping a (relatively) high carbon tax rate may become politically unfeasible, thus constraining policy-makers decisions and possibly reverting their past choices. Conversely, when social dynamics are introduced, whatever positive role preferences had in the internal case is substantially diluted, and browner preferences may even lead to the need for more reactive carbon taxation in the short term to reach the emission reduction targets fixed by the government.

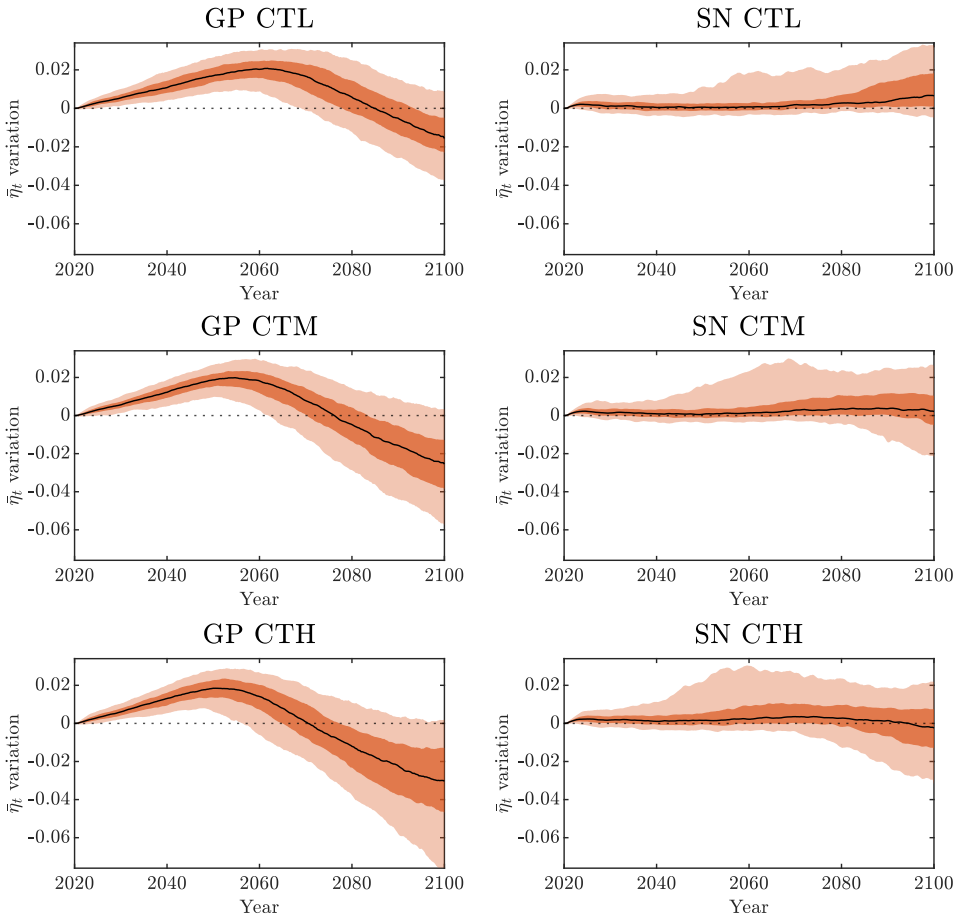


Figure 5: Weighted average green preferences ($\bar{\eta}_t$) variation.

Note: Sensitivity results for the carbon tax adjustment speed parameter ϵ^{CA}. Adjustment speed is lowest for the top figures and highest for the bottom figures. The figures on the left show the results for the *Carbon tax GP* experiment. The figures on the right show the results for the *Carbon tax SN* experiment. Variations are computed with respect to the baseline without abatement (see Tables 3 and 4).

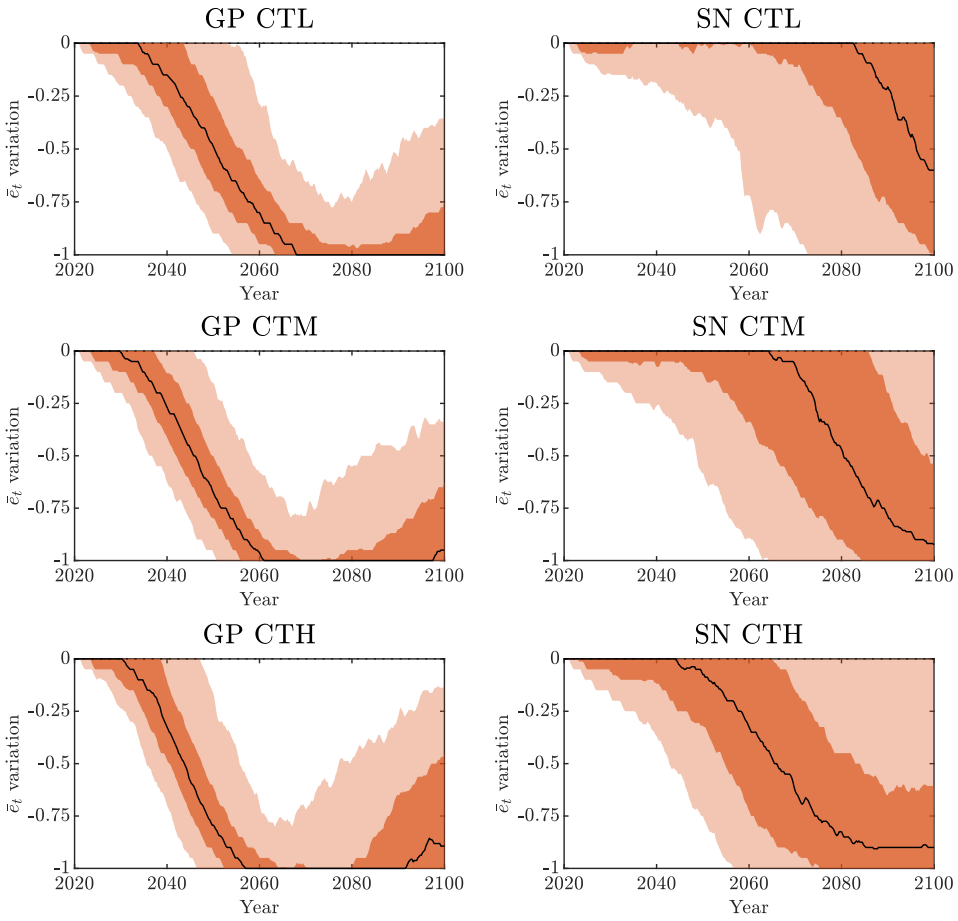


Figure 6: Mean Emission Intensity ($\bar{e}_t$) variation in the C-Sector.

Note: Sensitivity results for the carbon tax adjustment speed parameter ϵ^{CA}. Adjustment speed is lowest for the top figures and highest for the bottom figures. The figures on the left show the results for the *Carbon tax GP* experiment. The figures on the right show the results for the *Carbon tax SN* experiment. Variations are computed with respect to the baseline without abatement (see Tables 3 and 4).

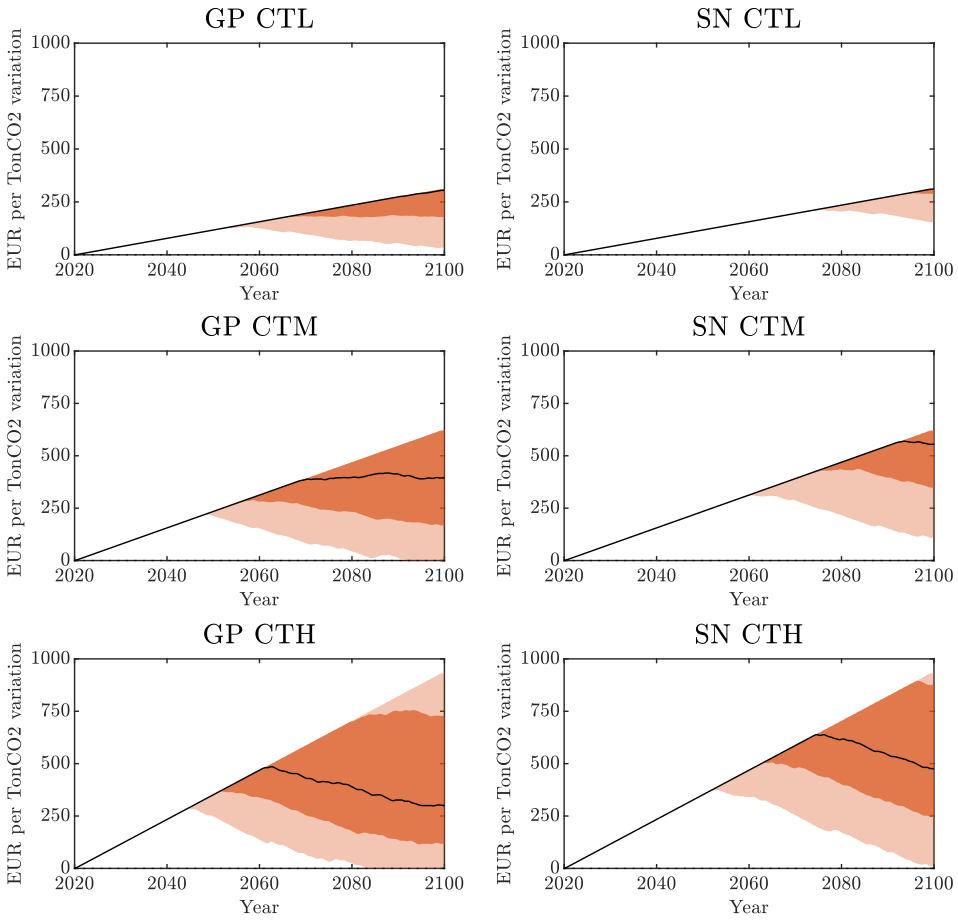


Figure 7: Carbon tax.

Note: Sensitivity results for the carbon tax adjustment speed parameter ϵ^{CA}. Adjustment speed is lowest for the top figures and highest for the bottom figures. The figures on the left show the results for the *Carbon tax GP* experiment. The figures on the right show the results for the *Carbon tax SN* experiment. Variations are computed with respect to the baseline without abatement (see Tables 3 and 4).

6 Conclusions

In this work, we apply an endogenous green preferences formation mechanism to the MATRIX model, testing a process by which households slowly adapt their pro-environmental attitude in accordance with their utility function. In this framework, we find that consumers have the power to prompt abatement investments, leading to a massive reduction in the emission intensity of firms even without public intervention guiding the effort with climate policy. We perform sensitivity analyses on the free parameters we introduce with this extension, showing that the environmental benefits are greater when the households

update their internal green preferences quickly or frequently.

Nevertheless, while this mechanism is complementary to carbon taxation in the short term, it becomes conflicting when emissions achieve the target level. Indeed, once the system reaches this point, consumers start suffering a loss of income due to carbon taxation without benefiting from a supplementary reduction in emissions, thus reversing their preferences (Bosetti et al., 2025). Indeed, the distributional consequences of climate policies are proving to be a major obstacle (the so called "green backlash") to public support for mitigation, with relevant implications on a political level (Egli et al., 2022; Colantone et al., 2024; Voeten, 2025; Stutzmann, 2024). However, parallel compensation schemes may prevent households from moving towards anti-environmental preferences or parties (Bolet et al., 2024; Colantone et al., 2024). In this sense, managing such a variation in households' attitudes while keeping a (relatively) high carbon tax rate may become politically unfeasible, thus constraining policy-makers decisions and possibly reverting their past choices. Still, further research in this direction is necessary, and future extensions to the MATRIX model could include the political process and its interaction with climate policy.

Those dynamics disappear when an imitative (i.e., social) component is introduced. Indeed, accounting for peers' preferences reduces the perceived reduction of firms' emissions intensities by consumers, and only coordinated and economy-wide changes would generate sufficient stimuli for households to modify their behavior. According to our sensitivity analysis, this happens even when imitation has a significantly lower weight in preference formation compared to the internal component, and the size of a household's neighborhood seems to have a limited impact on this effect.

Our results concerning the role of social influence seem counterintuitive, i.e., peer dynamics may slow down the green transition. Nevertheless, we model green preferences as continuous and unbounded, allowing consumers to adopt contrary, indifferent, or supportive behavior toward the green attributes of a product. This novelty explains the difference between our results and those found in existing literature, which often equate "indifference" to "brown preferences", thus reducing the complexity of the decision-making process. The innovation of having contrary-indifferent-supportive behavior and the potential non-linear effects on opinion dynamics are significant and can be deepened in further studies on peer influence in various contexts. For example, it could be applied to research on social support for environmental policies, where the spread of ideas and behaviors – such as conspiracy theories and non-scientific thinking – plays a crucial role.

However, this study presents some limitations. Firstly, our focus on macro-level abatement objectives leads us to exclude micro-level post-purchase green consumer habits. These may affect emissions but would also overly complicate the calibration process of a macro-ABM and imply the introduction of additional free parameters (as well as extensive sensitivity analyses). Furthermore, it is worth remembering that most global CO2 emissions come from industry and energy production (IPCC, 2023). Secondly, our assumptions concerning network structure and the initial distribution of green preferences may impact the dynamics of green preferences and their long-term value (Torren-Peraire et al., 2024).

Concerning the interaction of green preferences with climate policy, internal green preferences make the government's task easier and faster in the short term by reducing the need for carbon taxation. Then again, these advantages vanish once social dynamics are included. Thus, the government may be able to exploit green consumers to attain its emission reduction objectives. However, encouraging firms to jump-start abatement investments is necessary to allow consumers to find the green path. Some form of short-term financial assistance (such as subsidies or guarantees) to private investments in carbon capture and storage or strengthening the emission permits trading system are just a few options for the government to provide the momentum needed.

To summarize, our results support the capability of pro-environmental preferences to facilitate the green transition. However, when firms display a limited initial commitment to abatement, the diffusion process can be slowed down or even reversed if consumers give importance (no matter how little) to the green preferences exhibited by their peers. The positive signals from a few virtuous firms can drown among the contrasting opinions of one's network. Thus, we highlight the importance of massive, coordinated abatement efforts in the short term if policymakers intend to exploit pro-environmental preferences to their advantage. Slow and uncertain signals to consumers may be counterproductive.

References

Aghion, P., Bénabou, R., Martin, R., and Roulet, A. (2023). Environmental Preferences and Technological Choices: Is Market Competition Clean or Dirty? *American Economic Review: Insights*, 5(1):1–19.

Altafini, C. (2013). Consensus Problems on Networks With Antagonistic Interactions. *IEEE Transactions on Automatic Control*, 58(4):935–946.

Babutsidze, Z. and Chai, A. (2018). Look at me Saving the Planet! The Imitation of Visible Green Behavior and its Impact on the Climate Value-Action Gap. *Ecological Economics*, 146:290–303.

Banerjee, A., Breza, E., Chandrasekhar, A. G., and Mobius, M. (2021). Naïve Learning with Uninformed Agents. *American Economic Review*, 111(11):3540–3574.

Bazzana, D., Rizzati, M., Ciola, E., Turco, E., and Vergalli, S. (2024). Warming the MATRIX: Uncertainty and heterogeneity in climate change impacts and policy targets in the Euro Area. *Energy Economics*, 134:107585.

Bedard, S. A. N. and Tolmie, C. R. (2018). Millennials' green consumption behaviour: Exploring the role of social media. *Corporate Social Responsibility and Environmental Management*, 25(6):1388–1396.

Berardi, S. and Tedeschi, G. (2017). From banks' strategies to financial (in)stability. *International Review of Economics & Finance*, 47:255–272.

Bigler, P. and Janzen, B. (2023). Green Spills: Peer Effects in Pro-environmental Behaviors. *SSRN Electronic Journal*.

Binder, M. and Blankenberg, A.-K. (2017). Green lifestyles and subjective well-being: More about self-image than actual behavior? *Journal of Economic Behavior & Organization*, 137:304–323.

Bolet, D., Green, F., and Gonzalez-Eguino, M. (2024). How to get coal country to vote for climate policy: The effect of a "Just Transition Agreement" on Spanish election results. *American Political Science Review*, 118(3):1344–1359.

Bosetti, V., Colantone, I., De Vries, C. E., and Musto, G. (2025). Green backlash and right-wing populism. *Bocconi GREEN Working Paper*, 26.

Busato, F., Chiarini, B., Cisco, G., and Ferrara, M. (2022a). Green preferences. *Environment, Development and Sustainability*, 25(4):3211–3253.

Busato, F., Chiarini, B., Cisco, G., and Ferrara, M. (2022b). Green preferences. *Environment, Development and Sustainability*, 25(4):3211–3253.

Chai, A., Bradley, G., Lo, A., and Reser, J. (2015). What time to adapt? The role of discretionary time in sustaining the climate change value–action gap. *Ecological Economics*, 116:95–107.

Chan, Y. T. (2019). Optimal Environmental Tax Rate in an Open Economy with Labor Migration—An E-DSGE Model Approach. *Sustainability*, 11(19):5147.

Christakis, N. A. and Fowler, J. H. (2012). Social contagion theory: examining dynamic social networks and human behavior. *Statistics in Medicine*, 32(4):556–577.

Chwe, M. S.-Y. (2000). Communication and Coordination in Social Networks. *Review of Economic Studies*, 67(1):1–16.

Ciola, E., Turco, E., Gurgone, A., Bazzana, D., Vergalli, S., and Menoncin, F. (2023). Enter the MATRIX model:a Multi-Agent model for Transition Risks with application to energy shocks. *Journal of Economic Dynamics and Control*, 146:104589.

Colantone, I., Di Lonardo, L., Margalit, Y., and Percoco, M. (2024). The political consequences of green policies: Evidence from Italy. *American Political Science Review*, 118(1):108–126.

Deffuant, G., Neau, D., Amblard, F., and Weisbuch, G. (2000). Mixing beliefs among interacting agents. *Advances in Complex Systems*, 03(01n04):87–98.

Degroot, M. H. (1974). Reaching a Consensus. *Journal of the American Statistical Association*, 69(345):118–121.

DeMarzo, P. M., Vayanos, D., and Zwiebel, J. (2003). Persuasion Bias, Social Influence, and Unidimensional Opinions. *The Quarterly Journal of Economics*, 118(3):909–968.

Diaz-Rainey, I. and Ashton, J. K. (2010). Profiling potential green electricity tariff adopters: green consumerism as an environmental policy tool? *Business Strategy and the Environment*, 20(7):456–470.

Dickinson, J. L., Crain, R. L., Reeve, H. K., and Schuldt, J. P. (2013). Can evolutionary design of social networks make it easier to be 'green'? *Trends in Ecology & Evolution*, 28(9):561–569.

Dietz, T. and Rosa, E. A. (1994). Rethinking the Environmental Impacts of Population, Affluence and Technology. *Human Ecology Review*, 1(2):277–300.

Dietz, T. and Rosa, E. A. (1997). Effects of population and affluence on CO2 emissions. *Proceedings of the National Academy of Sciences*, 94(1):175–179.

Dimant, E. (2019). Contagion of pro- and anti-social behavior among peers and the role of social proximity. *Journal of Economic Psychology*, 73:66–88.

Douenne, T. and Fabre, A. (2020). French attitudes on climate change, carbon taxation and other climate policies. *Ecological Economics*, 169:106496.

Douenne, T. and Fabre, A. (2022). Yellow Vests, Pessimistic Beliefs, and Carbon Tax Aversion. *American Economic Journal: Economic Policy*, 14(1):81–110.

Egli, F., Schmid, N., and Schmidt, T. S. (2022). Backlash to fossil fuel phase-outs: the case of coal mining in US presidential elections. *Environmental Research Letters*, 17(9):094002.

Ek, K. (2005). Public and private attitudes towards "green" electricity: the case of Swedish wind power. *Energy Policy*, 33(13):1677–1689.

Frank, R. H. (1985). The Demand for Unobservable and Other Nonpositional Goods. *The American Economic Review*, 75(1):101–116.

Friedkin, N. E. and Johnsen, E. C. (1990). Social influence and opinions. *The Journal of Mathematical Sociology*, 15(3–4):193–206.

Ghosh, M. (2019). Determinants of green procurement implementation and its impact on firm performance. *Journal of Manufacturing Technology Management*, 30(2):462–482.

Granovetter, M. (1978). Threshold Models of Collective Behavior. *American Journal of Sociology*, 83(6):1420–1443.

Harbaugh, W. T., Mayr, U., and Burghart, D. R. (2007). Neural Responses to Taxation and Voluntary Giving Reveal Motives for Charitable Donations. *Science*, 316(5831):1622–1625.

Hartin, C. A., Patel, P., Schwarber, A., Link, R. P., and Bond-Lamberty, B. P. (2015). A simple object-oriented and open-source model for scientific and policy analyses of the global climate system – hector v1.0. *Geoscientific Model Development*, 8(4):939–955.

Hegselmann, R. and Krause, U. (2002). Opinion Dynamics and Bounded Confidence: Models, Analysis and Simulation. *Journal of Artificial Societies and Social Simulation*, 5(3).

Hsieh, C.-S., Deer, L., Koenig, M., and Vega-Redondo, F. (2023). Social networks and collective action in large populations: An application to the Egyptian Arab Spring. CEPR Discussion Papers 18093, C.E.P.R. Discussion Papers.

IPCC (2023). *Sections. In: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland.*

Jackson, M. O. and Yariv, L. (2007). Diffusion of Behavior and Equilibrium Properties in Network Games. *American Economic Review*, 97(2):92–98.

Jackson, T., University of Surrey, C. f. E. S., of Surrey. Centre for Environmental Strategy, U., and Network, S. D. R. (2005). Motivating Sustainable Consumption: A Review of Evidence on Consumer Behaviour and Behavioural Change. Technical report, Guildford.

Joshi, Y., Uniyal, D. P., and Sangroya, D. (2021). Investigating consumers' green purchase intention: Examining the role of economic value, emotional value and perceived marketplace influence. *Journal of Cleaner Production*, 328:129638.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263.

Knox, F. and McElroy, M. B. (1984). Changes in atmospheric CO2: Influence of the marine biota at high latitude. *Journal of Geophysical Research: Atmospheres*, 89(D3):4629–4637.

Konc, T., Drews, S., Savin, I., and van den Bergh, J. C. (2022). Co-dynamics of climate policy stringency and public support. *Global Environmental Change*, 74:102528.

Kotchen, M. J. and Moore, M. R. (2007). Private provision of environmental public goods: Household participation in green-electricity programs. *Journal of Environmental Economics and Management*, 53(1):1–16.

Lackner, T., Fierro, L. E., and Mellacher, P. (2025). Opinion dynamics meet agent-based climate economics: An integrated analysis of carbon taxation. *Journal of Economic Behavior & Organization*, 229:106816.

Lenton, T. M. (2000). Land and ocean carbon cycle feedback effects on global warming in a simple Earth system model. *Tellus B: Chemical and Physical Meteorology*, 52(5):1159.

Lipari, F., Lázaro-Touza, L., Escribano, G., Sánchez, A., and Antonioni, A. (2024). When the design of climate policy meets public acceptance: An adaptive multiplex network model. *Ecological Economics*, 217:108084.

MacKerron, G. J., Egerton, C., Gaskell, C., Parpia, A., and Mourato, S. (2009). Willingness to pay for carbon offset certification and co-benefits among (high-)flying young adults in the UK. *Energy Policy*, 37(4):1372–1381.

Maestre-Andrés, S., Drews, S., and van den Bergh, J. (2019). Perceived fairness and public acceptability of carbon pricing: a review of the literature. *Climate Policy*, 19(9):1186–1204.

Mastroeni, L., Vellucci, P., and Naldi, M. (2019). Agent-Based Models for Opinion Formation: A Bibliographic Survey. *IEEE Access*, 7:58836–58848.

Mueller-Frank, M. and Neri, C. (2013). Social Learning in Networks: Theory and Experiments. *SSRN Electronic Journal*.

Mukonza, C. and Swarts, I. (2019). The influence of green marketing strategies on business performance and corporate image in the retail sector. *Business Strategy and the Environment*, 29(3):838–845.

Nguyen, H. V., Nguyen, C. H., and Hoang, T. T. B. (2018). Green consumption: Closing the intention-behavior gap. *Sustainable Development*, 27(1):118–129.

Peattie, K. (2010). Green Consumption: Behavior and Norms. *Annual Review of Environment and Resources*, 35(1):195–228.

Perusset, F. (2025). Consumer Preferences and Green Transition. *Available at SSRN 5040831*.

Rhodes, E., Axsen, J., and Jaccard, M. (2017). Exploring Citizen Support for Different Types of Climate Policy. *Ecological Economics*, 137:56–69.

Rizzati, M. C. P., Ciola, E., Turco, E., Bazzana, D., and Vergalli, S. (2025). Beyond Green Preferences: Demand-side and Supply-side Drivers in the Low-Carbon Transition. *Environmental and Resource Economics*, 88(5):1239–1295.

Roe, B., Teisl, M. F., Levy, A., and Russell, M. (2001). US consumers' willingness to pay for green electricity. *Energy Policy*, 29(11):917–925.

Rowlands, I. H., Scott, D., and Parker, P. (2003). Consumers and green electricity: profiling potential purchasers. *Business Strategy and the Environment*, 12(1):36–48.

Sangroya, D. and Nayak, J. K. (2017). Factors influencing buying behaviour of green energy consumer. *Journal of Cleaner Production*, 151:393–405.

Steger, M. F., Kashdan, T. B., and Oishi, S. (2008). Being good by doing good: Daily eudaimonic activity and well-being. *Journal of Research in Personality*, 42(1):22–42.

Stutzmann, S. (2024). The electoral consequences of the coal phase-out in Germany. Technical report, Working Paper Series of the Cluster The Politics of Inequality.

Sælen, H. G. and Aasen, M. (2023). Exploring public opposition and support across different climate policies: Poles apart? *Ecological Economics*, 209:107838.

Takahashi, T., Sutherland, S. C., Wanninkhof, R., Sweeney, C., and ... de Baar, H. J. (2009). Climatological mean and decadal change in surface ocean pCO2, and net sea–air CO2 flux over the global oceans. *Deep Sea Research Part II: Topical Studies in Oceanography*, 56(8–10):554–577.

Tam, K.-P. and Chan, H.-W. (2023). Conspiracy theories and climate change: A systematic review. *Journal of Environmental Psychology*, 91:102129.

Torren-Peraire, D., Savin, I., and van den Bergh, J. (2024). An Agent-Based Model of Cultural Change for a Low-Carbon Transition. *Journal of Artificial Societies and Social Simulation*, 27(1).

Turco, E., Bazzana, D., Rizzati, M., Ciola, E., and Vergalli, S. (2023). Energy price shocks and stabilization policies in the MATRIX model. *Energy Policy*, 177:113567.

Viscusi, W. K. and Zeckhauser, R. J. (2006). The Perception and Valuation of the Risks of Climate Change: A Rational and Behavioral Blend. *Climatic Change*, 77(1–2):151–177.

Voeten, E. (2025). The energy transition and support for the radical right: Evidence from the Netherlands. *Comparative Political Studies*, 58(2):394–428.

Wang, B., Zeng, D., and Yang, B. (2021). Decomposing peer effects in pro-environmental behaviour: Evidence from a Chinese nationwide survey. *Journal of Environmental Management*, 295:113100.

Waytz, A., Zaki, J., and Mitchell, J. P. (2012). Response of Dorsomedial Prefrontal Cortex Predicts Altruistic Behavior. *The Journal of Neuroscience*, 32(22):7646–7650.

Wei, C., Chiang, C., Kou, T., and Lee, B. C. Y. (2017). Toward Sustainable Livelihoods: Investigating the Drivers of Purchase Behavior for Green Products. *Business Strategy and the Environment*, 26(5):626–639.

Weisbuch, G., Deffuant, G., Amblard, F., and Nadal, J. (2002). Meet, discuss, and segregate! *Complexity*, 7(3):55–63.

Yang, M., Chen, H., Long, R., and Yang, J. (2022). The impact of different regulation policies on promoting green consumption behavior based on social network modeling. *Sustainable Production and Consumption*, 32:468–478.

Yu, X., Gao, Z., and Zeng, Y. (2014). Willingness to pay for the "Green Food" in China. *Food Policy*, 45:80–87.

Zarnikau, J. (2003). Consumer demand for 'green power' and energy efficiency. *Energy Policy*, 31(15):1661–1672.

Zeng, Y., Dong, P., Shi, Y., Wang, L., and Li, Y. (2020). Analyzing the co-evolution of green technology diffusion and consumers' pro-environmental attitudes: An agent-based model. *Journal of Cleaner Production*, 256:120384.

A Appendix

Here we include the basic functioning of the matrix model that is not directly relevant to the research question of this chapter, for further details refer to Ciola et al. (2023), Bazzana et al. (2024), and Rizzati et al. (2025).

A.1 Sequence of events

The model follows the sequence of events adopted by Bazzana et al. (2024), except for the absence of climate damages, the new additions are highlighted in italics:

- Firms inherit production goals, prices, and input demands from the previous period.
- If climate policy is binding, the government tweaks carbon pricing, and firms evaluate abatement decisions.
- Inputs markets and production:
  - Labor: inelastic work supply from households meets firms' demands. Workers pay taxes and set apart their consumption budget.
  - Fossil fuels: the sector monopolist provides fossil fuel to firms.
  - Energy: energy services are the output of E-firms' production process, which combines fossil fuel, labor, and capital goods. Then, energy is dispatched to C-firms and K-firms.
  - Consumption goods: energy services, fossil fuels, labor, and capital stock are employed by C-firms to produce consumption goods. The goods are subsequently sold to households.
  - *Green preferences: households review their green preferences by the endogenous process comprising the internal and the imitation factors. At the end of the procedure, firms enter the market and are able to select the firm providing the most utility according to their new criteria.*
  - Capital goods: energy services, fossil fuels, and labor contribute to the production of capital goods in K-firms. Capital is then sold to both C-firms and E-firms.
- Expected prices and quantities are updated.
- Firms compute profits, pay taxes to the government and dividends to entrepreneurs when due. In addition, they need to repay the banks with a share of outstanding debt.
- Firms in financial distress (either due to insolvency or illiquidity) resort to their owner's resources to remediate, if these are not enough, they default, and new firms are reinitialized in their stead.

- Firms compute input demand for the next time step, accounting for their current resources and expectations, potentially tapping into the credit market if necessary.
- Banks compute profits and identify NPL, triggering their default procedure when its conditions are met.
- The government enforces a fiscal sustainability rule, adapting the tax rate and social transfers.
- The central bank sets the policy rate implied by its Taylor rule.
- Climate module: firms' emissions are updated, then feeding the climate module, which determines a change in mean global temperature.

A.2 Firms

Firms do not have a perfect knowledge of the market, nor they are able to know their demand function. However, they do form expectations on future demand based off their past experience. Therefore, in this model, there is no such thing as a price-quantity combination that leads to market equilibrium, but rather, each firm learns and adapts its price-quantity strategy $\{P, Q\}$ in order to improve its own performance.

Market conditions and strategic interaction determine price and quantity adjustments carried out by firms at each time step, by the means of an evolutionary algorithm of price-quantity setting with strategic complementarities (Ciola et al., 2023). More in detail, firms first resort to imitation, by adopting the same strategy as a similar, more profitable competitor, then, if no suitable candidate is found, they explore a neighborhood of their current $\{P, Q\}$ strategy, according to past excess demand.

Thus, first a target competitor is selected by adopting $d_{f,s,t}$ as a measure of distance between the selected firm and all other firms $s \neq f \in \mathcal{N}^F$ of the same kind (i.e., operating in the same sector). That distance is obtained by means of a logit model computed as the difference between firms' relative production:

$$d_{f,s,t} = \left| \hat{y}_{f,t} - \hat{y}_{s,t} \right|, \tag{A.1}$$

with normalized production $\hat{y}_{f,t}$ determined as follows:

$$\hat{y}_{f,t} = \frac{P_{f,t}Q_{f,t} - \min\left(P_{f,t}Q_{f,t}\right)}{\max\left(P_{f,t}Q_{f,t}\right) - \min\left(P_{f,t}Q_{f,t}\right)}. \tag{A.2}$$

Then, a competitor S is sampled from the list of all firms, The probability of being picked is decreasing with distance $d_{f,s,t}$ (i.e., their similarity). Eventually, the firm updates price and quantity $\{P_{f,t+1}, Q^*_{f,t+1}\}$ according to the following rules:

$$Q^*_{f,t+1} = \begin{cases} \zeta^Q Q^*_{f,t} + \left(1 - \zeta^Q\right) Q_{S_t} & \text{if } \Pi_{S,t} \geq \Pi_{f,t} \\ \zeta^Q Q^*_{f,t} + \left(1 - \zeta^Q\right) \hat{Q}_{f_t} & \text{otherwise} \end{cases}, \tag{A.3}$$

$$P_{f,t+1} = \begin{cases} \zeta^P P_{f,t} + \left(1-\zeta^P\right) P_{S_t} & \text{if } \Pi_{S,t} \geq \Pi_{f,t} \\ \zeta^P P_{f,t} + \left(1-\zeta^P\right) \hat{P}_{f_t} & \text{otherwise} \end{cases}. \tag{A.4}$$

In other words, if a firm's competitor is more profitable ($\Pi_{S,t} \geq \Pi_{f,t}$), then the firm moves its strategy towards the competitor's strategy $P_{s,t}, Q_{s,t}$, with speed ζ^P and ζ^Q, for price and quantity, respectively. If the opposite is true (i.e., a firm's target competitor is less profitable), the firm explores a neighborhood $\hat{P}_{f,t}, \hat{Q}_{f,t}$ of their current price-quantity combination, by drawing a random number from a uniform distribution, whose sign is determined by excess demand or supply (positive and negative, respectively).

Firms carry out production by employing a CES technology characterized by constant returns to scale and diminishing marginal returns. Thus, they adopt the following production function:

$$Q_{f,t} = \left[\sum_{j=1}^{n} A_{j,f,t} \left(X_{j,f,t}\right)^{\rho_f}\right]^{\frac{1}{\rho_f}}, \tag{A.5}$$

where $X_{j,f,t}$ represents the amount of input $j = 1, ..., n$, employed by firm f at each time step t. Factor shares vary sector by sector, and they are specified by parameters $A_{j,f}$ (with $\sum_{j=1}^{n} A_{j,f,0} = 1$). Parameter $\rho_f = (\sigma_f - 1)/\sigma_f$ is the substitution parameter, a function of Hicks elasticity of substitution σ_f.

Given future desired production $Q^*_{f,t+1}$, expectations on input prices $\{\mathbb{E}_{f,t}\left[P_{j,t+1}\right]\}_{j=1}^{n}$, and the technological constraint, each firm determines its conditional demand for each input by minimizing the expected direct costs $\mathbb{E}_{f,t}\left[DC_{f,t+1}\right]$, accordingly:

$$\begin{aligned} \min_{\{X_{f,j,t+1}; \Delta X_{f,j,t+1}\}_{j=1}^{J}} \mathbb{E}_{f,t}\left[DC_{f,t+1}\right] &= \sum_{j=1}^{n} \mathbb{E}_{f,t}\left[P_{j,t+1} \Delta X_{f,j,t+1}\right], \\ \text{s.t. } Q^*_{f,t+1} &= \left[\sum_{j=1}^{J} A_{j,f,t+1} \left(X_{j,f,t+1}\right)^{\rho_f}\right]^{\frac{1}{\rho_f}}, \\ X_{j,f,t+1} &= \Delta X_{j,f,t+1} + \left(1-\delta_j\right) X_{j,f,t}, \\ \Delta X_{j,f,t+1} \geq 0 \quad &\text{when } j \text{ indicates physical capital,} \end{aligned} \tag{A.6}$$

with $\Delta X_{j,f,t+1}$ being the additional input demand, and δ_j the depreciation rate. Moreover, in the case of labor and fossil fuels, we impose exogenous productivity growth at a fixed rate ζ^{growth}. Thus, factor shares $A_{j,f,t}$ (with j being labor and fossil fuel) are constantly updated to account for the increase in productivity:

$$A_{j,f,t} = A_{j,f,t-1} \left(1 + \zeta^{growth}\right)^{\frac{\sigma_f - 1}{\sigma_f}}. \tag{A.7}$$

It follows that the firm's nominal input demand for the next period is:

$$H^d_{j,f,t+1} = \mathbb{E}_{f,t}\left[P_{j,t+1}\right] \left[\left(\frac{A_{j,f,t+1}\psi_{f,t+1}}{\mathbb{E}_{f,t}[P_{j,t+1}]}\right)^{\sigma_f} Q^*_{f,t+1} - \left(1-\delta_j\right) X_{j,f,t}\right] \quad \forall j = 1, ..., n, \tag{A.8}$$

where $\psi_{f,t+1}$ are the expected marginal costs obtained as:

$$\psi_{f,t+1} = \left[\sum_{j=1}^{n} \left(\mathbb{E}_{f,t} \left[P_{j,t+1} \right] \right)^{1-\sigma_f} \left(A_{j,f,t+1} \right)^{\sigma_f} \right]^{\frac{1}{1-\sigma_f}}. \tag{A.9}$$

If internal liquidity is not enough to face expected direct costs, then the firm resorts to the decentralized credit market. In subsequent periods, the firm repays the principal on outstanding loans at a fixed instalment rate, with the possibility to refinance all its loans at every period with the new interest rate. In the case even external resources are not enough to meet production goals, then firms maximize production by choosing the optimal combination of inputs with their new constraint.

After sales take place firms are able to compute profits by subtracting operating and financing expenses from revenues, as well as the costs of the abatement technology and taxes (including carbon taxation from climate policy when active). Solvent firms then go on to pay dividends to entrepreneurs, while insolvent (if their net worth is negative) or illiquid (if their deposits are negative) firms face bankruptcy. In the case of illiquidity, a firm can still survive if its entrepreneur has enough personal wealth to make ends meet. Defaulted firms are replaced by new ones. After their creditors attempt to partially recover their loans by tapping into residual deposits, the entrepreneurs employ their personal resources to reacquire the old firms' assets at their historical cost, potentially resorting to a new credit line to cover the costs. Nevertheless, the old firms' creditors record a loss equal to the previous outstanding loans, net of recovered deposits and refinancing of the new firm.

A.3 Banks

Interest rates are computed by banks as the sum of the central bank policy rate i_t^{CB}, a component adjusting rates for the bank's relative size ($NW_{b,t} / \max_{s=1,\ldots,\mathcal{N}^B} NW_{s,t}$), such that larger banks (i.e., with a larger net worth $NW_{b,t}$) can apply lower rates, and two additional risk factors, as follows:

$$i_{b,f,t} = i_t^{CB} + \varrho^B \left(1 - \frac{1 - NW_{b,t}}{\max_{s=1,\ldots,\mathcal{N}^B} NW_{s,t}} \right) + \rho^B \frac{L_{f,t}}{NW_{f,t}} + \iota^B \frac{NPL_{t-1}}{L_{t-1}}, \tag{A.10}$$

where the first risk factor captures firm-specific risk by employing its leverage as a metric (i.e., the outstanding loans to net worth ratio $L_{f,t}/NW_{f,t}$). The second risk factor pertains to the bank's solidity, by accounting for the amount of non-performing loans the bank holds (NPL_{t-1}) in relation to total loans (L_{t-1}). The impact of each risk factor is captured by scale parameters ϱ^B, ρ^B, and ι^B, for dimensioning, firm-related risk, and bank solidity, respectively.

Banks' profits are increasing with interests on loans, while they are negatively affected by non-performing loans, as described by:

$$\Pi_{b,t} = \sum_{f=1}^{\mathcal{N}^f} i_{b,f,t} L_{b,f,t} - \sum_{f \in \mathcal{D}^F} NPL_{b,f,t}, \tag{A.11}$$

with $\mathcal{D}^F$ being the set of defaulted firms linked to the bank. Profitable banks go on to pay dividends to their entrepreneurs. Macroprudential regulation under the Basel III framework controls the maximum amount of debt $L_{b,t}^{max}$ a bank can issue at each time period by enforcing a capital requirement set by the regulator:

$$L_{b,t}^{max} = \frac{NW_{b,t}}{\gamma^B} \frac{1}{\omega^B}, \tag{A.12}$$

where $\gamma^B \in (0,1)$ is the capital adequacy ratio (CAR) and ω^B the risk-weight on corporate loans. Furthermore, the legal lending limit $L_{b,f,t}^{max}$, contains the exposure of each bank b towards a single firm f, by limiting the amount of credit it can supply to a κ^B fraction of its current net worth:

$$L_{b,f,t}^{max} = \kappa^B NW_{b,t}. \tag{A.13}$$

When their equity no longer meets the macroprudential requirements listed above, the bankers first try to recapitalize the overexposed bank and avoid default. In case the banker does not possess enough personal wealth to successfully recapitalize the bank, then the latter goes bankrupt. In this scenario, the government bears the losses, and recapitalization is achieved by resorting to public expenditure.

A.4 The central bank

The policy rate i_t^{CB} is set by the central bank by adopting the following Taylor rule:

$$i_t^{CB} = \rho^{CB} i_{t-1}^{CB} + \left(1 - \rho^{CB}\right) \max\left[0, r^* + p^* + \lambda^y \left(u^* - u_{t-1}\right) + \lambda^p \left(p_{C,t-1} - p^*\right)\right], \tag{A.14}$$

where ρ^{CB} is the speed of adjustment to the previous policy rate, to smooth the transition towards the new policy regime, while p^* and u^* are the target level of inflation and unemployment, respectively. Parameter r^* is the steady-state interest rate, while λ^p and λ^y determine the intensity of the central bank's reaction in targeting inflation and unemployment, respectively.

A.5 The climate module

In this extension, contrary to Bazzana et al. (2024), we are not interested in the role of climate damages, since we excluded its direct feedback with green preferences, and it is not directly relevant to abatement investments. However, we are interested in how abatement investments and carbon taxation may interact with endogenous green preferences and, in turn, how green preferences can affect mitigation. Thus, we apply the HECTOR carbon cycle (Hartin et al., 2015) to model the impact of the increase in the stock of CO2 emissions on global mean temperature. More specifically, the stock of carbon stored in the atmosphere ($C_{atm,t}$) evolves as follows:

$$C_{atm,t} = C_{atm,t-1} + F_{A,t} - F_{L,t} - F_{O,t}, \tag{A.15}$$

a function of anthropogenic emissions F_A, carbon exchange between atmosphere-land modules F_L, and between the atmosphere-ocean modules F_O. Simply put, HECTOR consists of three modules, determining the amount of carbon in the atmosphere by accounting for carbon flows between atmosphere, land, and oceans.

Anthropogenic emissions F_A are obtained as the sum of the endogenous emissions produced by the model representing the Euro area economy and an exogenous component, according to equation 23.

Carbon exchange between atmosphere and land $F_{L,t}$ is determined by the land box. This module comprises three layers representing vegetation, detritus, and soil, each of them connected to the others and directly to the atmosphere, as follows:

$$F_{L,t} = NPP_t - RH_{d,t} - RH_{s,t}, \tag{A.16}$$

thus, the $F_{L,t}$ factor depends on net primary production (NPP) of carbon dioxide net of heterotrophic respiration of the soil and detritus layers ($RH_{s,t}$ and $RH_{d,t}$, respectively).

Net primary production accounts for CO2 intake in the vegetation layer and the amount released by it through photosynthesis and respiration, the process is governed by the following equation:

$$NPP_t = NPP_0 \left[1 + \beta^{npp} \log\left(\frac{C_{atm,t-1}}{C_{atm,0}}\right)\right], \tag{A.17}$$

with β^{npp} being a constant carbon fertilization parameter, and $C_{atm,t-1}/C_{atm,0}$ the variation in global carbon stock in the atmosphere relative to its pre-industrial value ($C_{atm,0}$), while NPP_0 is the initial value of net primary production. The heterotrophic respiration factor $RH_{y,t}$ (where $y \in \{s, d\}$ denote soil and detritus, respectively), on the other hand, is a function of a biome-specific value Q_{10}, to allow heterogeneous local temperature feedback (i.e., temperature changes in a biome may differ from the global mean), and a moving average of past temperatures, to represent the slower transmission of heat through soil layers, accordingly:

$$RH_{y,t} = C_{y,t} f_{ry} Q_{10}^{\frac{T_{t-1}}{10}} \tag{A.18}$$

The land carbon stocks (C_v for vegetation, C_d for detritus, and C_s for soil) evolve with land-use change fluxes as follows:

$$C_{v,t} = NPP_t f_{nv} + C_{v,t-1}\left(1 - f_{vd} - f_{vs}\right), \tag{A.19}$$

$$C_{d,t} = C_{d,t-1}\left(1 - f_{ds}\right) + NPP_{t-1} f_{nd} + C_{v,t-1} f_{vd} - RH_{d,t}, \tag{A.20}$$

$$C_{s,t} = C_{s,t-1} + NPP_{t-1} f_{ns} + C_{v,t-1} f_{vs} + C_{d,t-1} f_{ds} - RH_{s,t}, \tag{A.21}$$

where partitioning fractions f (the first subscript stands for the source of the transfer, while the second subscript identifies its destination, with r being respiration, n NPP, v vegetation, d detritus, and s soil) account for carbon flows from vegetation to soil and detritus.

Finally, the ocean carbon cycle (Knox and McElroy, 1984; Lenton, 2000; Takahashi et al., 2009), relates ocean-atmosphere carbon exchange to individual ocean surface flows:

$$F_{i,t} = \phi K h_{i,t} A r_i S c_{i,t}^{-\frac{1}{2}} U_{10}^2 \Delta p CO_2 \tag{A.22}$$

with pCO_2 being the atmosphere-ocean gradient of the partial pressure, ϕ a unit conversion constant, $Kh_{i,t}$ Henry's Law constant, Ar_i the area of the surface layer, U_10 average wind speed, and $Sc_{i,t}$ Schmidt number. Subscript $i = \{HL, LL\}$ in case of high and low latitude oceans, respectively. High and low latitude ocean surface temperatures are a linear function of global mean temperature, and the gradient between their values is the source of carbon dioxide exchange from LL towards HL. HECTOR's initialization requires initial assumptions about physical properties of the ocean module, flows of water between the ocean boxes are considered constant, in order to obtain the steady state level of carbon stocks. Likewise, other assumptions regarding the initial physical and chemical state of the system are drawn from Lenton (2000). An ocean chemistry subsystem provides the values for pCO_2, $Sc_{i,t}$, and $Kh_{i,t}$ at each time step. Moreover, CO2 exchange between layers of the same ocean is a function of water mass exchanged, as well as carbon stocks in each layer involved, and their respective volumes.

At the end of the process, the variation in global atmospheric mean temperature is a function of total radiative forcing RF, a climate feedback parameter λ, and the ocean heat absorption coefficient k_h, accordingly:

$$\Delta T_t = \frac{\lambda}{1 + k_h} RF \tag{A.23}$$

All parameters concerning the HECTOR carbon cycle and their description are listed in the Appendix A.9 (see Bazzana et al. (2024), for specific sources for each parameter).

A.6 Additional results

Here we check for the correlation between $\bar{\eta}_t$ and the detrended real GDP series finding that changes in green preferences with social dynamics mimic those in real GDP (Figure 9). The same does not occur when only the internal component is at work. This could mean that the main drivers of green preferences in the presence of social dynamics are real income and consumption, while observed emission intensities become irrelevant. Indeed, looking at Figure 9 we compare the dynamics of $\bar{\eta}_t$ for a randomly selected simulation for a *SN-Base* (the *Myopic – Medium imitation* scenario from the *SN Sensitivity* experiment in Table 2) scenario on the left, and a *GP-Base* (the *Switching probability – Regular* scenario from the *GP Sensitivity* experiment in Table 1) scenario on the right (for the same simulation seed). The green preferences are shown along with the unemployment rate and the average net worth, real GDP, wage index growth rates time series. In the SN-Base case, the cycles in $\bar{\eta}_t$ values mirror the macro-series, with unemployment rates following by a few quarters. Real GDP and average real net worth are the most in synchronous with $\bar{\eta}_t$ variations, while real wages fluctuations anticipate the response in green preferences. However, the dynamics of $\bar{\eta}_t$ in the right-hand side panels (*GP-Base*

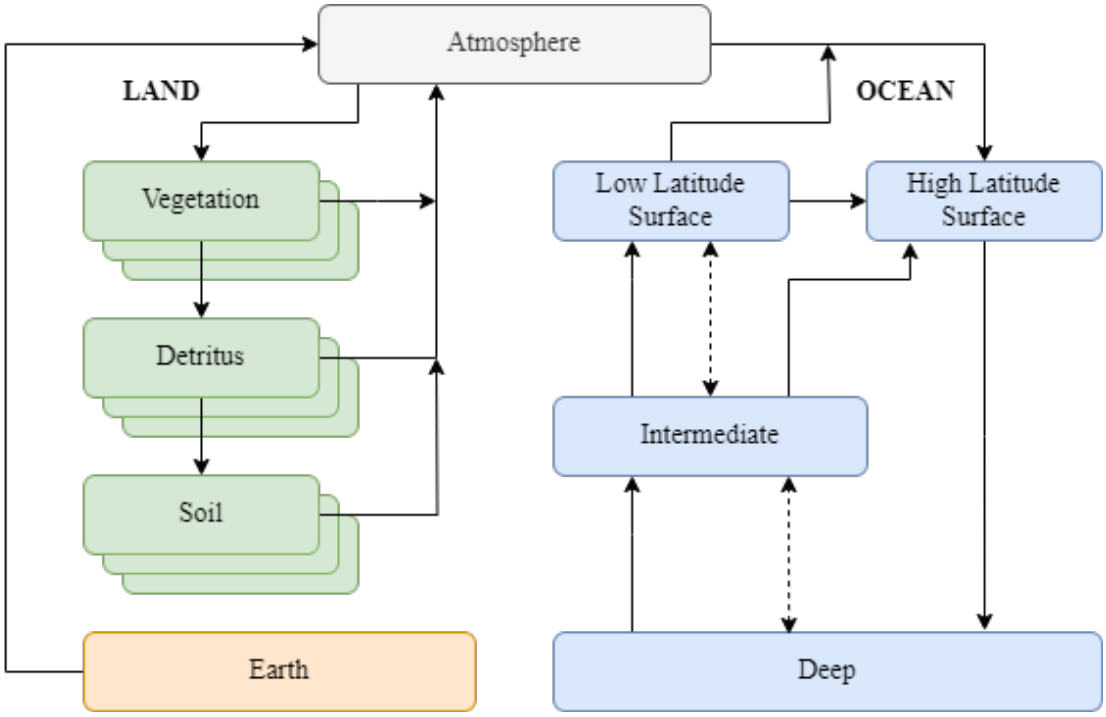


Figure 8: Flow chart of the HECTOR carbon cycle.

Source: Hartin et al. (2015)

case) show disconnect from the main macro-series. In this scenario its value is more dependent on abatement progress. After the attainment of the environmental goals set, green preferences decline and start displaying some degree of cyclicality.

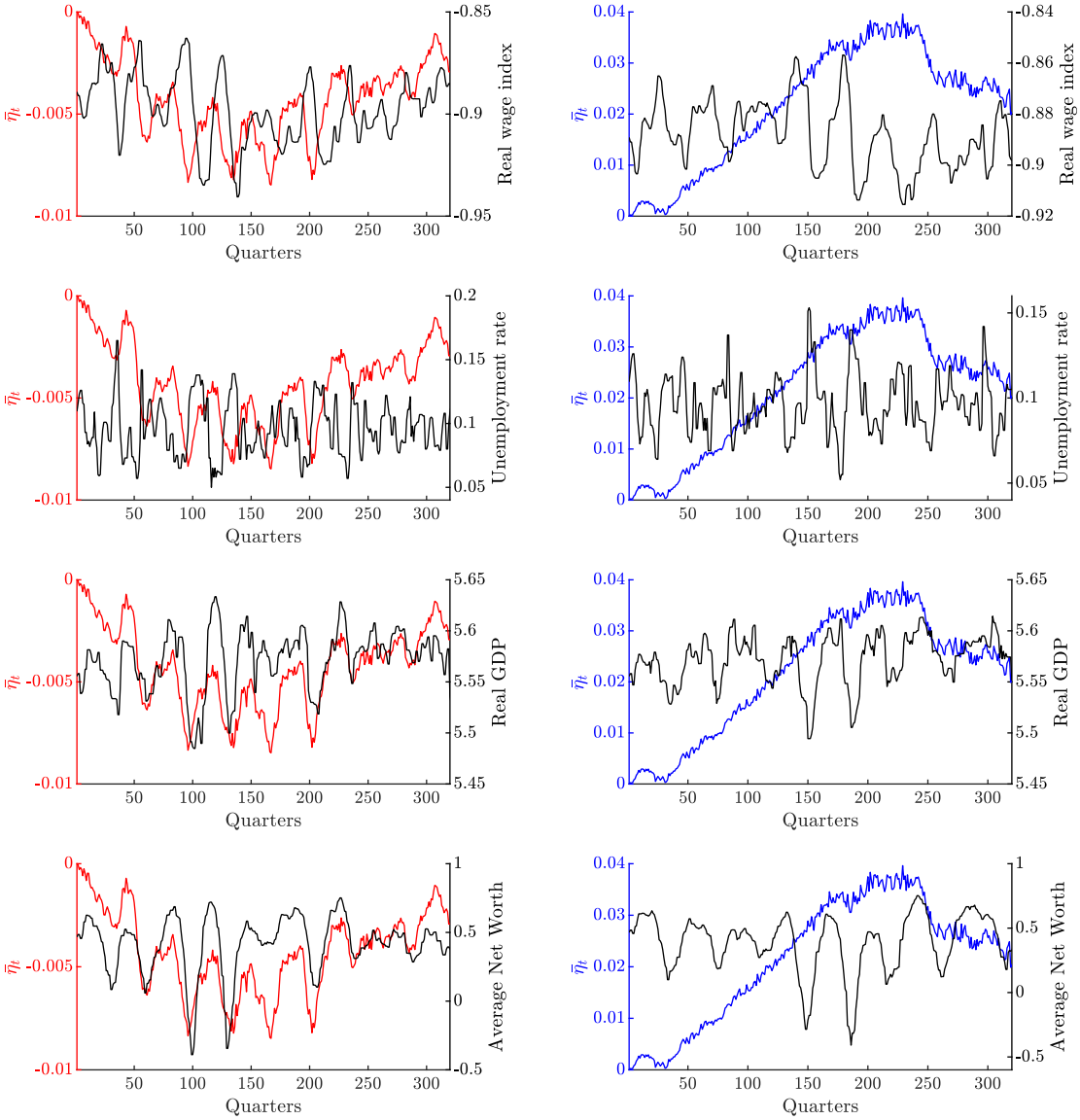


Figure 9: Plots of macro-variables and $\bar{\eta}_t$ for a randomly sampled simulation.

Note: Real GDP (in log form) has been detrended by subtracting the exogenous quarterly growth rate ζ^{growth}. The *SN scenario* is shown on the left, in red, while the *GP scenario* is on the right, in blue. The first quarter corresponds to 2020Q1.

Then we analyze the cross-correlations of the cycle components of $\bar{\eta}_t$ and the main macro-series. Figure 10 shows the results for the *SN-Base* scenario, highlighting the procyclicality of green preferences with real GDP, and average net worth. As previously observed, wages anticipate $\bar{\eta}_t$ dynamics. Figure 11 shows the results for the *GP-Base* scenario, where all the cross-correlations displayed are much milder compared to the

previous case, maintaining the same cyclical properties.

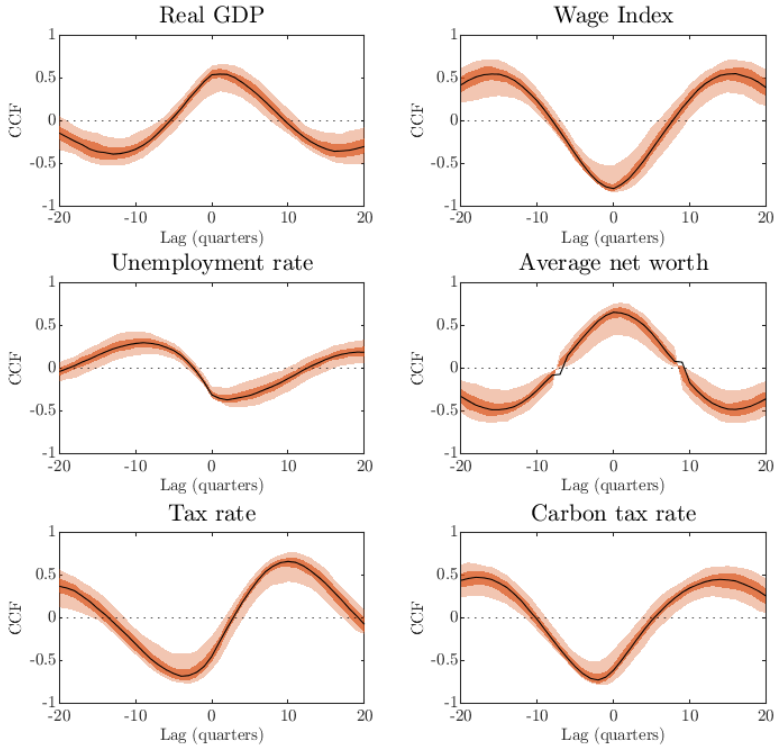


Figure 10: Cross-correlations of $\bar{\eta}_t$ with financial macro-series (*SN-base* scenario).

Note: the series have been dentrended by using the Hodrick-Prescott filter ($\lambda = 16000$).

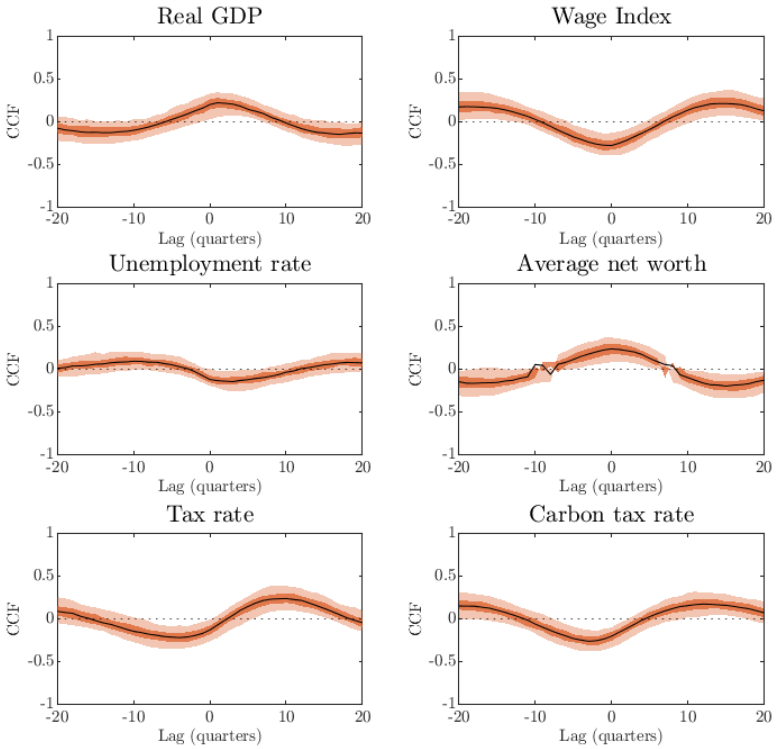


Figure 11: Cross-correlations of $\bar{\eta}_t$ with financial macro-series (*GP-base* scenario).

Note: the series have been dentrended by using the Hodrick-Prescott filter ($\lambda = 16000$).

Finally, Figure 12 shows the distribution for $\bar{\eta}_t$ at the end of the simulation for the *GP Base* and *SN Base* scenarios. The distribution is obtained by pooling together the final distributions from all 250 Monte Carlo simulations. In both cases the mean is close to zero, but dispersion is significantly more pronounced when the social component is not active. When social dynamics are introduced, green preferences tend to converge towards a slightly negative value of η, although the distribution appears to be somewhat right-skewed.

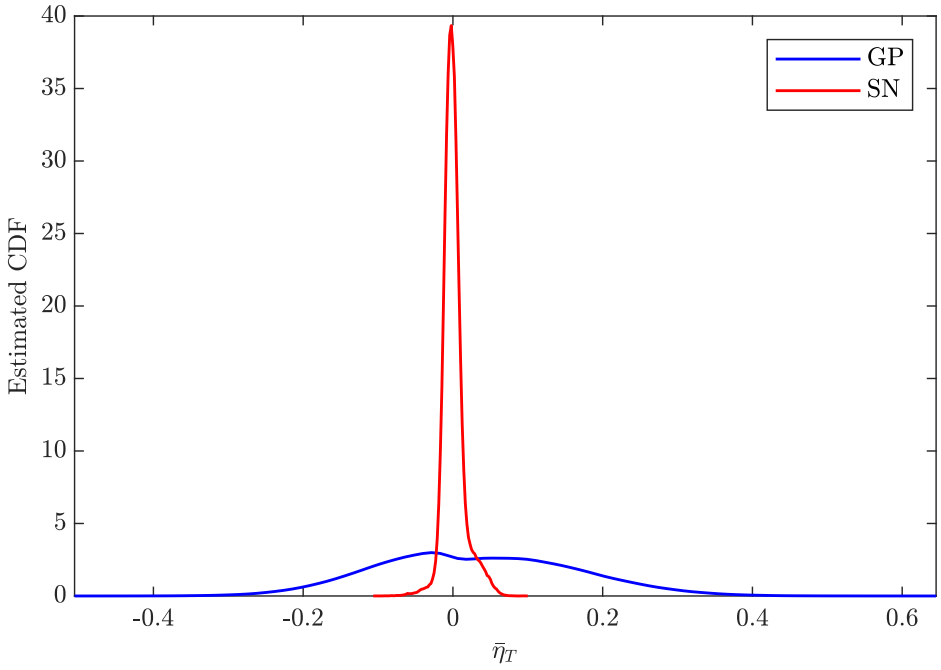


Figure 12: Kernel smoothing function estimate of $\bar{\eta}_t$ at time T.

Note: Distribution in the value of green preferences at the end of all simulations in case of *SN-base* (red) and *GP-base* (blue) scenarios.

A.7 Stock-flow consistency

Table A.1: Aggregate balance sheet.

	Households	**E-firms**	**C-Firms**	**K-Firms**	**Banks**	**Government**	**Central bank**	Σ
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	$-NW_h$	$-NW_e$	$-NW_c$	$-NW_k$	$-NW_b$	$-NW_g$		0
Σ	0	0	0	0	0	0	0	

Table A.2: Aggregate transaction flows.

	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
Abatement	Ab	$-Ab_e$	0	$-Ab_c$	0	$-Ab_k$	0	0	0	0	$+Ab\,(-Ab)$	0	0	0
Energy	0	$+E$	0	$-E_c$	0	$-E_k$	0	0	0	0	0	0	0	0
Fossil fuel	$+\,(1-\eta_0)\,F$	$-F_e+\eta_0 F$	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
Carbon taxes	0	$-CT_e$	0	$-CT_c$	0	$-CT_k$	0	0	0	0	0	$+CT$	0	0
Loan interests	0	$-iL_e$	0	$-iL_c$	0	$-iL_k$	0	$+iL$	0	0	0	0	0	0
Bond 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

A.8 MATRIX model parameters

Table A.3: General Parameters.

Parameter	Description	Value
β^C	Discount rate households	0.996
β^F	Discount rate firms	0.980
γ^{PQ}	Maximum size of price-quantity exploration	0.050
ζ^Q	Speed of adjustment of quantities	0.750
ζ^P	Speed of adjustment of prices	0.750
ω	Intensity of choice	10
ε	Household memory parameter	β^C
χ	Marginal propensity to consume out of wealth	$1 - \beta^C$
η^F	Firms dividend payout rate	$1 - \beta^C$
ζ^{growth}	Exogenous quarterly growth rate	0.018/4

Table A.4: Wage Update.

Parameter	Description	Value
θ^W	Insider-outsider bargaining power	0.510
ρ^W	Wage stickiness	0.560
ι^W	Inflation anchoring	0.670

Table A.5: Firms parameters.

Parameter	**Description**	**Value**
$\mathcal{N}^C$	Number of consumption good firms	100
δ_N	Labor depreciation	1
δ_C	Depreciation rate of consumption goods	1
σ_C	Elasticity of substitution (C-firms)	0.25
$A_{N,C}$	Factor share labor (C-firms)	0.69
$A_{E,C}$	Factor share energy (C-firms)	0.03
$A_{K,C}$	Factor share capital (C-firms)	0.25
$A_{O,C}$	Factor share natural resources (C-firms)	0.03
$\mathcal{Z}^C$	Maximum number of new partners (C-market)	0.25
$\mathcal{N}^E$	Number of energy firms	10
δ_E	Depreciation of energy services	1
σ_E	Elasticity of substitution (E-firms)	0.25
$A_{N,E}$	Factor share labor (E-firms)	0.33
$A_{O,E}$	Factor share natural resources (E-firms)	0.39
$A_{K,E}$	Factor share capital (E-firms)	0.28
$\mathcal{Z}^E$	Maximum number of new partners (E-market)	4
δ_O	Foreign natural resource depreciation rate	1
η^O	Share of foreign natural resource going to E-firms	0.80
ν^O	Foreign natural resource expenditure over GDP	0.021
$\mathcal{N}^K$	Number of capital good firms	60
δ_K	Depreciation rate of capital goods	0.0125
σ_K	Elasticity of substitution (K-firms)	0.25
$A_{N,K}$	Factor share labor (K-firms)	0.91
$A_{E,K}$	Factor share energy (K-firms)	0.04
$A_{O,K}$	Factor share natural resources (K-firms)	0.05
$\mathcal{Z}^K$	Maximum number of new partners (K-market)	4

Table A.6: Banks parameters.

Parameter	Description	Value
$\mathcal{N}^B$	Number of banks	10
γ^B	Capital adequacy ratio	0.08
κ^B	Maximum single exposure to borrowers	0.25
ρ^B	Interest rate setting parameter: firm leverage	0.017/4
ι^B	Interest rate setting parameter: bank soundness	0.001/4
ϱ^B	Interest rate setting parameter: share of aggregate NPL	0.029/4
θ^B	Share of loans repaid at each quarter	0.0125
ω^B	Risk weighting	1
$\mathcal{Z}^B$	Maximum number of new partners (credit market)	0.2

Table A.7: Workers and consumption.

Parameter	Description	Value
$\mathcal{N}^W$	Number of workers	1000
$\mathcal{N}^F$	Number of entrepreneurs	$\mathcal{N}^C+\mathcal{N}^E+\mathcal{N}^K+\mathcal{N}^B$
$\mathcal{N}^H$	Number of consumers	$\mathcal{N}^W+\mathcal{N}^F$
$\mathcal{Z}^N$	Maximum number of new partners (labor market)	10

Table A.8: Monetary policy.

Parameter	Description	Value
p^*	Inflation target	0.02/4
u^*	Unemployment rate target	0.087
r^*	Steady state real interest rate	$1/\beta^C-1$
λ^p	Weight of inflation in monetary policy	1.41
λ^u	Weight of unemployment in monetary policy	0.11
ρ^{CB}	Speed of adjustment of monetary policy	0.85

Table A.9: Government.

Parameter	Description	Value
b^*	Target debt-GDP ratio	0.75
ρ^G	Speed of adjustment to debt-GDP ratio target	0.007
ψ^G	Share of social expenditures	0.094

Table A.10: Climate Policy and Emissions.

Parameter	Description	Value
ϵ^{CA}	Speed of carbon tax adjustment (BAU)	0.02
$\bar{E}^{CA}$	Share of the emission hard target	0.25
e^C	Relative emission intensity (C-sector)	1
e^E	Relative emission intensity (E-sector)	1.4
e^K	Relative emission intensity (K-sector)	0.47

Table A.11: Abatement.

Parameter	Description	Value
J^{AbT}	Max number of abatement steps	20
$\hat{e}^{AbT}$	Max abatement potential	1
θ^{AbT}	Probability of new technology adoption	1

Table A.12: Green Preferences Sensitivity Analysis.

Parameter	Description	Value
ν^{GP}	Adjustment speed of green preferences	$0.005; 0.010; 0.015$
$\|K\|$	Number of neighbors observed at each time step	$2; \mathcal{N}^H - 1$
ϕ^{Gp}	Weight of internal preferences vs imitation process	$1.00; 0.75; 0.50; 0.25$
θ^{GP}	Switching probability of green preferences to the new value	$0.25; 0.50; 0.75; 1.00$

Table A.13: Simulation parameters.

Parameter	Description	Value
T	Time horizon, the periods from the transient phase are then eliminated	1500
MC	Number of Monte Carlo simulations	250

A.9 HECTOR parameters

Refer to Bazzana et al. (2024) for the sources of the climate module parameters.

Table A.14: HECTOR Parameters - Carbon.

Parameter	Description	Value
$C_{atm,0}$	Atmospheric carbon GtC	588.1
$C_{D,0}$	Initial carbon in detritus GtC	55.2941
$C_{S,0}$	Initial carbon in soil GtC	1808.8235
$C_{V,0}$	Initial carbon in vegetation GtC	500
$C_{HL,0}$	Initial carbon in high latitude ocean surface GtC	138.72
$C_{LL,0}$	Initial carbon in low latitude ocean surface GtC	723.15
$C_{IO,0}$	Initial carbon in intermediate ocean surface GtC	8309.75
$C_{DO,0}$	Initial carbon in deep ocean GtC	26383.65
$F_{L,0}$	Atmosphere-land steady state carbon flux	0.0
$F_{O,0}$	Atmosphere-ocean steady state carbon flux	0.0

Table A.15: HECTOR Parameters - Land.

Parameter	Description	Value
NPP_0	Initial Net Primary Production GtC	50.0
f_{ds}	Fraction of detritus carbon transferred to soil	0.6
f_{nd}	Fraction of NPP carbon transferred to detritus	0.6
f_{ns}	Fraction of NPP carbon transferred to soil	0.05
f_{nv}	Fraction of NPP carbon transferred to vegetation	0.35
f_{rd}	Fraction of respiration carbon transferred to detritus	0.25
f_{rs}	Fraction of respiration carbon transferred to soil	0.02
f_{vd}	Fraction of vegetation carbon transferred to detritus	0.034
f_{vs}	Fraction of vegetation carbon transferred to soil	0.001
β^{npp}	Carbon fertilization parameter	0.36
Q_{10}	Terrestrial respiration temperature response	2.45

Table A.16: HECTOR Parameters - Temperature.

Parameter	Description	Value
$T_{t,0}$	Average temperature preindustrial level	14
λ_C	Equilibrium climate sensitivity	1.2
γ_{rf}	Radiative forcing coefficient	5.35
k_h	Ocean heat uptake efficiency	1.16
$T_{HL,0}$	Temperature of high latitude ocean surface	2.0
$T_{LL,0}$	Temperature of low latitude ocean surface	22.0

Table A.17: HECTOR Parameters - Ocean.

Parameter	**Description**	**Value**
alk_{hl}	Alkalinity levels high latitude ocean box μmol/kg	229×10^{-6}
alk_{ll}	Alkalinity levels low latitude ocean box μmol/kg	2246×10^{-6}
ϕ	Unit conversion parameter	0.585
U_h	Wind speed in ocean surface	6.7
S	Ocean average salinity	34.5
α_h	Henry's constant, solubility parameter of CO2	0.727
$E_{LI}k_wd$	Low to intermediate latitude water mass exchange m^3s^{-1}	2.08×10^8
$E_{LI}k_wi$	Intermediate to deep latitude water mass exchange m^3s^{-1}	1.25×10^8
k_{ols}	Thermohaline circulation m^3s^{-1}	7.2×10^7
k_{ohs}	High latitude circulation m^3s^{-1}	4.9×10^7

Table A.18: HECTOR Parameters - Areas and Components.

Parameter	**Description**	**Value**
spy	Seconds per year μmol/kg	31557600
A_{ohs}	Fraction area of high latitude ocean	0.15
A_{ols}	Fraction area of low latitude ocean	0.85
V_{ohs}	High latitude surface volume m^3	5.4×10^{15}
V_{ols}	Low latitude surface volume m^3	3.6×10^{16}
V_{ode}	Intermediate ocean volume m^3	9.64×10^{17}
V_{oin}	Deep ocean volume m^3	3.24×10^{17}

Contact.

MIT CEEPR Working Paper Series
is published by the MIT Center for Energy and Environmental Policy Research from submissions by affiliated researchers.
For inquiries and/or for permission to reproduce material in this working paper, please contact:

General inquiries: ceepr@mit.edu
Media inquiries: ceepr-media@mit.edu

MIT CEEPR

Center for Energy and
Environmental Policy Research

MIT Center for Energy and
Environmental Policy Research
Massachusetts Institute of Technology
77 Massachusetts Avenue, E19-411
Cambridge, MA 02139-4307
USA

ceepr.mit.edu

MASSACHUSETTS INSTITUTE OF TECHNOLOGY