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Prevention first vs. cap-and-trade policies in an agent-based integrated assessment model with GHG emissions permits

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Prevention first vs. *cap-and-trade* policies in an agent-based integrated assessment model with GHG emissions permits

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Abstract

In this work, we ask whether tradable emissions permits, based on the *cap-and-trade* principle, provide better climate change and economic projections than alternative regulations for GHG emissions, such as operational permits which are commonly used to mitigate non-GHG emissions (*prevention first* principle). Towards this goal, we simulate climate and the economy through a new version of the Dystopian Schumpeter meeting Keynes (DSK) model, extended to include an emission trading system (ETS) and operational permit systems. We show that climatic and economic projections in an ETS scenario need not be superior to those in an operational permit scenario. Which system delivers more encouraging projections on temperature anomalies, the green transition, and economic dynamics depends on institutional details, such as the set of firms for which permits are mandatory; the regulatory requirement of corrective measures; the magnitude of penalties; the stringency of the ETS. An ETS with a declining number of permits emerges as the best-performing system in terms of macroeconomic, microeconomic, and climate outcomes. A system of operational permits mandatory only for large firms (centralised permits) ranks as the second-best system, provided that the regulator imposes corrective measures regarding R&D expenses and machinery replacement.

Keywords: Climate change; Environmental permits; Emissions trading system; Polluter pays principle; Agent-based models; Macro-economic dynamics.

JEL classification numbers: C63; Q40; Q50; Q54

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1 Introduction

For years, permits have been the main instrument to foster the environmental sustainability of economic activities. In most countries, industrial producers and infrastructure developers need to obtain an environmental permit or license before their operations can begin. Environmental permit systems have been legally adopted in almost all countries in the world (Reid, 2008; Huppes and Simonis, 2009). However, mainstream economic theory has argued that environmental costs can be internalised by means of an appropriate system of property rights, paving the way to the set up of environmental markets centred on tradable emission allowances. Carbon emissions trading is nowadays among the most discussed pillars of climate policy (Tvinnereim and Mehling, 2018; Green, 2021; Stoll and Mehling, 2021; Hong et al., 2022). In the European Union, the emissions trading system (EU-ETS) includes around 10,000 installations in the power sector and manufacturing industry, covering around 40% of total GHG emissions from the 27 EU countries. Yet, the evidence suggests that despite the EU-ETS in place, investments in renewable energy sources (RES) have not accelerated. Considering pre-pandemic years, 2017 and 2018 witnessed a drop in new investments up to -14% (FS-UNEP, 2019; IEA, 2019), despite the falling levelised costs of electricity from RES (in 2008-2018, -81% for solar PV, -46% for onshore wind according to FS-UNEP (2019).

Against these data, EU-ETS and more generally carbon emissions trading have raised criticisms. Together with the flourishing academic literature on EU-ETS design in recent years (see Verbruggen et al., 2019, for a review), it has been noticed that the goal of carbon trading is to reduce emissions, not to avoid them. The EU-ETS mandates that industrial plants need to surrender emission allowances corresponding to the amount of GHG they emit, but as long as firms can afford to pay for the extra allowances, they do not need to mitigate their climate impact. This runs against the *prevention first* principle stated in the *"Hierarchy of action on pollution"* developed by the European Commission, that should be implemented by design and during production (see Commission, 2021).

Coincidentally, the EU in 2020 has started a process of revising its Industrial Emissions Directive (IED, 2010/75/EU), a piece of legislation that fully endorses the *prevention first* principle, resulting in a revision proposal published in April 2022 (COM/2022/156 final/3). Under the IED, pollution prevention is achieved by setting emissions limits for all pollutants before installations are able to operate, as well as other requirements such as energy efficiency. In this system, "operational permits" are granted, depending on how the predicted negative impacts will be mitigated or whether additional requirements are fulfilled (i.e., paying for the damage according to a "polluter pays principle"). Installations covered under the IED Directive amount to more than 50.000 in the EU. The IED covers the largest emitters of GHG in the EU, yet GHG emission limit values are currently excluded for installations falling under the Emissions Trading System Directive (ETSD), according to Art. 9 IED, presumably in order to avoid duplicate regulation.[1]

[1] In the UK, environmental permitting is regulated by Regulations 2016 SI 2016/11542 (EPR) and applies to England and Wales. It is meant to regulate Emission activities, installations and mobile plants, as well as waste operations and materials facilities (limiting on asbestos, titanium dioxide, petrol vapour recovery). Another debated example of environmental permitting is Brazil. It mainly relies on "command and control" CONAMA Resolution No.237/1997 regulating environmental licensing of mining, mechanics, manufacturing, chemical, and pipeline industries.

Such a gap in the legislation and the fear it could hinder climate policy effectiveness have led a number of environmental associations and think tanks, such as ClientEarth and CarbonMarketWatch, among others, to advocate the inclusion of GHG emission limits in the IED.[2] This would implement the prevention first principle for GHG emissions and exploit the complementarities between the cap-and-trade principle and the prevention principle (see e.g. Reis et al., 2022). Still, these regulations may as well increase the time, costs, and risks associated with opening and operating a business. In this sense, there may be a trade-off between emission prevention on the one hand, and productive investments and employment opportunities on the other.

This given, it is an open question whether climate change and economic projections would improve if GHG were to fall under the IED (*prevention first*) as opposed to being regulated by an ETS (*cap-and-trade*). More generally, a systematic, model-based analysis is still missing about the comparative climate and economic performances of ETS and operational permit systems, in a framework that views the economy as a complex, interacting system. Exploring this research question may provide new insights in the debate on market-based and command-and-control policy approaches, as in Lamperti et al. (2020).

In order to provide an answer, we simulate climate and the economy through a new version of the Dystopian Schumpeter meeting Keynes (DSK) model that enriches the original Lamperti et al. (2018) model with scenarios including an emission trading system (ETS) and operational permit systems. To the best of our knowledge, agent-based models including GHG emissions trading systems have mainly explored the effects of ETS on energy markets (see e.g. Richstein et al., 2014; Chappin and Dijkema, 2009; Weidlich et al., 2008, and the review in Castro et al. (2020)). Effects on macroeconomic indicators have seldom been assessed through agent-based models. The few instances that we have found make assumptions at odds with the complexity of climate-economy interactions, such as general equilibrium (e.g. Tang et al., 2015) or exogenous aggregate demand (e.g. Fang and Ma, 2020). This is a surprising gap in the literature, in light of the considerable interest in the effects of emissions permit systems on output and employment, as shown by the evidence in Arlinghaus (2015). These considerations open a wide scope for agent-based modelling and assessment of the effects of permits on GHG emissions and macroeconomic indicators, also in light of the paucity of ETS policy evaluations (see Green, 2021).

We have found the following results. First of all, we show that climatic and economic projections in an ETS scenario need not be superior to an operational permit scenario. As shown by our results and sensitivity analyses, which system delivers more encouraging projections on temperature anomalies, the green transition, and economic dynamics depends on institutional details, such as the set of firms for which permits are mandatory (*centralised permits* if only large firms are obliged, *decentralised permits* if all firms need to comply); the regulatory requirement of corrective

[2] ClientEarth was consulted as part of a Targeted Stakeholders Survey. Its responses are available at `https://www.clientearth.org/media/of0p2ull/clientearth_ied-revision_response-to-targeted-stakeholder-survey_april2021.pdf`. The feedback from CarbonMarketWatch can be found here: `https://carbonmarketwatch.org/publications/cmws-feedback-to-the-european-commissions-consultation-on-industrial-emissions-eu-rules-updated/`.

measures; the magnitude of penalties; the stringency of the ETS in terms of supplied allowances and compliance costs. An ETS with a declining number of permits emerges as the best-performing system in terms of macroeconomic, microeconomic, and climate outcomes. A system of centralised permits with corrective measures regarding R&D expenses and machinery replacement ranks as the second-best system.

This may appear, *prima facie*, as a negative toll for the system based on the prevention first principle. Indeed, in the model, operational permits impose costs on emitters, in terms of penalties or corrective measures, without rewarding the most virtuous producers. Moreover, corrective measures prescribed by the existing regulations are criticised by several stakeholders for imposing costs while requiring actions characterised by uncertain payoffs (such as increasing R&D). Hence, it is remarkable that despite these drawbacks, operational permits fall short of ETS by only a modest gap. Such a gap may be even smaller under more realistic assumptions about ETS. Supporters of moving GHG emissions under the IED may have a point.

The remainder of the paper is organised as follows. Section 2 describes the model. In Section 3, after performing empirical validation, we present and compare climate and economy projections in scenarios including an emissions trading system and operational permits. Finally, Section 4 concludes and discusses future extensions.

2 The model

Our model represents an economy populated by heterogeneous, interacting agents and a climate box directly inherited from Lamperti et al. (2018, 2020). Climate and the economy evolve simultaneously and the links between the two are modelled non-linearly and stochastically.[3] Figure **??** provides a graphical representation of the DSK model, with the integrations that characterise the present model. The model is composed of two vertically separated industrial sectors (blue boxes in the diagram), where firms are fuelled by an energy sector (orange box) and receive loans from a financial sector composed of a unique bank in the system (grey box). Firms invest in R&D, innovate, and imitate to improve the performances of the machines they produce. Firms in all of the three sectors (capital goods, consumption goods, energy) are monitored by a regulatory authority (green ellipse), which requires periodic reports on non-financial performance, imposes maximum ceilings (either on individual or sectoral bases) on GHG emissions and levies penalties on firms violating the limits. Firms in different industries also engage in emission trading. Both the energy and industrial sectors emit CO_2, whose concentrations in the atmosphere affect the evolution of the climate. As in Lamperti et al. (2018), the carbon cycle characterised by feedback loops in the relationship with the Earth's radiative forcing and the global mean surface temperature. The impact of an increase in the atmospheric temperature on economic dynamics is modelled through a stochastic, time-evolving, disaster-generating function akin to Lamperti et al. (2018).[4]

[3] The DSK model's direct ancestors are Dosi et al. (2010, 2013).

[4] The model also allows analyses of the impact of different climate shocks on the system (dashed lines in the diagram), which are not included in this paper version but will be considered in future developments.

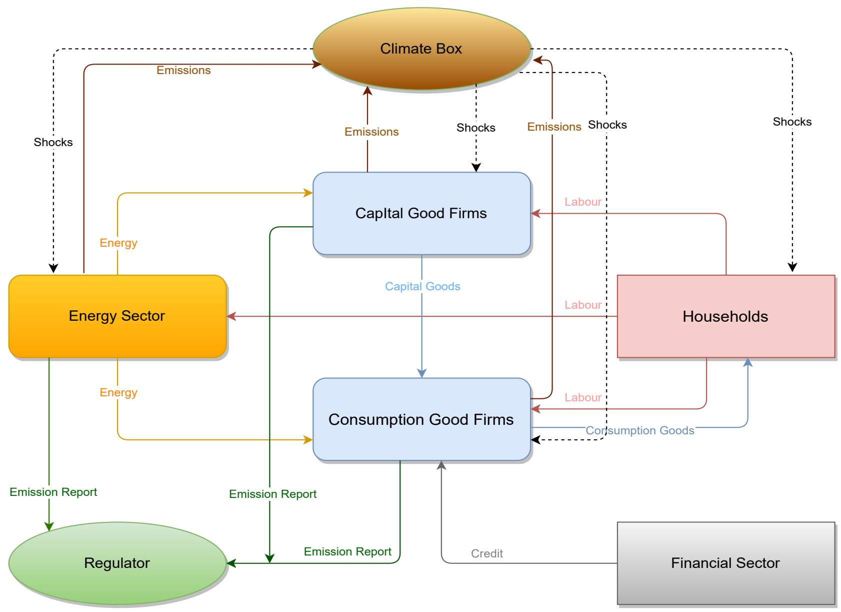

Figure 1: The structure of the model

2.1 Industry: Consumption and capital good sectors

Our economy includes a capital-good (firms indexed by i) and consumption-good sectors (firms indexed by j), which are vertically related by the supply of machines. Firms in the capital-good industry produce machine-tools using labour and energy. The vintages of produced machines are characterized by different labour productivity, energy efficiency and environmental friendliness upon which the unit cost is computed (see the details in Appendix A.1). Production technologies and machines generate CO2 emissions indirectly through their electricity consumption and directly through environmental friendliness. The latter refers to the number of polluting substances the firm emits in each time period for each unit of energy used in the production process.

Firms in the capital-good industry adaptively strive to increase market shares and profits by upgrading their technologies via innovation and imitation (see Dosi et al., 2010), modelled as a two-step process described in Appendix A.3. Innovation and imitation are costly: firms invest in R&D a fraction of their past sales and split the amount invested between search for innovation and attempts to imitate more technologically advanced competitors. The technical change affects all the three dimensions that characterise machines in the model, namely, *productivity of labour*, *energy efficiency* and *environmental-friendliness*. Machines and techniques are characterised by their degree of environmental friendliness, which corresponds to the amount of GHG they emit in each period for each unit of energy employed throughout the production process.

Consumer good-firms produce a homogeneous good using their stock of machines, energy, and labour under constant returns to scale. Then, consumers spend all their available income buying good which is produced.[5] Firms plan their production according to adaptive demand expectations. They decide on their desired production level based on expected demand, desired inventories, and their stock of inventories following the rules in Appendix A.2. Whenever the capital stock is not sufficient to produce the desired amount, firms invest in order to expand their production capacity, and may thus acquire machines of a more recent vintage than the ones they already have. Machines are supplied by capital-good firms and labour productivities in the consumption-good industry evolve according to the technology embedded in the capital stock of each firm. Consumption-good firms choose their capital-good supplier by comparing the price, productivity, and energy-efficiency of the currently manufactured machine tools they are aware of.

Machine-tool firms advertise their machines' price and productivity levels by sending *brochures* to a subset of consumption-good firms, which in turn choose the machines with the lowest price and unit cost of production. In particular, let $\Xi_i(t)$ the set of all machines' vintages firm j have at time t. Then a machine of vintage τ is replaced with a new one if

$$\frac{p^{new}}{c_j^{con}(t) - c^{new}} = \frac{p^{new}}{\left[\frac{w(t)}{A_{i,\tau}^L} + \frac{c^{en}(t)}{A_{i,\tau}^{EE}}\right] - c_j^{new}} \leq b, \tag{1}$$

where p^{new} and c^{new} are the price and unitary cost of production associated to the new vintage of machines and b is a parameter determining firms' reluctance to invest. Machine production is a time-consuming process: consumption-good firms receive the ordered machines at the end of the period. The gross investment of each firm is the sum of expansion and replacement investments. Aggregate investment is the sum of the investments of all consumption good firms.

Pricing follows a variable markup rule. Firms set the price of the final good they produce according to

$$p_j^{con}(t) = c_j^{con}(t)[1 + \mu_j(t)], \tag{2}$$

where

$$\mu_j(t) = \mu_j(t-1)\left[1 + \upsilon\frac{f_j(t-1) - f_j(t-2)}{f_j(t-2)}\right], \tag{3}$$

with $0 \leq \upsilon \leq 1$. In equation (3), $f_j(t)$ indicates the market share of firm j at time t. Consumption-good firms have to finance their investments as well as their production. In line with a large body of literature (Stiglitz and Weiss, 1981; Greenwald and Stiglitz, 1993) we assume imperfect capital markets. Firms access firstly their net worth and if the latter does not fully cover total production and investment costs, they borrow external funds from the bank. However, firms have limited borrowing capacity: the ratio between debt and sales cannot exceed a maximum threshold depending on the firms' past sales. Moreover, credit rationing might occur. As described in Appendix A.4, the bank allocates total credit to each consumer-good sector firm on a pecking order basis, according to the ratio between net worth and sales. In particular, it first ranks firms on the basis of their net

[5] Details about the consumption decisions, wages and public expenditures can be found in Appendix A.5.

worth-to-sales ratio and starts to satisfy their demand. If the total credit available is insufficient to fulfill the demand of all the firms in the pecking order list, some firms that are lower in the ranking are credit rationed. Note that only firms that are not credit-rationed can fully satisfy their investment plans by employing their stock of liquid assets first and then their borrowing capacity. The maximum amount of credit available in the economy is set above the sum of firms' deposits by a multiplicative rule (Dosi et al., 2013). We assume the bank can lend money up to a threshold multiple of the firms' deposits for prudential reasons.

2.2 The energy sector

Energy production is performed by a vertically-integrated profit-seeking monopolist through power plants using green and dirty technologies.[6] The energy firm produces and sells electricity to firms in the capital-good and consumption-good industries, on demand. Hence, at the beginning of period t, electricity-consuming firms send orders that in aggregate amount to $D_e(t)$. The non-storable nature of electricity implies that the demand-supply balance must be continuously guaranteed. Profits of the energy monopolist at the end of period t are equal to

$$\Pi_e(t) = S_e(t) - PC_e(t) - IC_e(t) - RD_e(t). \tag{4}$$

In the above: $S_e(t)$ denotes the revenues from selling energy at a price $p_e(t)$ to satisfy demand $D_e(t)$, i.e. $S_e(t) \equiv p_e(t)D_e(t)$; $PC_e(t)$ is the total cost of generating an amount $D_e(t)$ of energy; $IC_e(t)$ is the cost of expansion and replacement investments; $RD_e(t)$ is the R&D expenditure. Each term is defined in detail in the Appendix A.6.

The energy producer adds a fixed markup $\mu_e \geq 0$ on the average cost of the most expensive infra-marginal plant. Hence the selling price reads $p_e(t) = \mu_e$ if $D_e(t) \leq K_{ge}(t)$, and $p_e(t) = \overline{c}_{de}(\tau, t) + \mu_e$, if $D_e(t) > K_{ge}(t)$, where $\overline{c}_{de}(\tau, t) = \max_{\tau \in IM} c_{de}(\tau, t)$. By setting a markup on this unit cost level, the energy producer gains a positive net revenue on all infra-marginal plants.

Energy sold to the capital-good industry is paid in advance, hence the stock of liquid assets of the energy monopolist is driven by the following dynamics:

$$NW_e(t) = NW_e(t-1) + \Pi_e(t) - cI_e(t), \tag{5}$$

where $cI_e(t)$ is the amount of internal funds used by the energy monopolist for investment and production purposes ($cI_e(t) \leq NW_e(t-1)$).

The energy producing firm needs to replace obsolete plants, as well as to perform expansion investments whenever the current capacity is insufficient to cover demand. New plants are built in house, but the costs of building new green and dirty plants differ. Specifically, no costs are born for new dirty plants, whereas a cost of IC^{τ}_{ge} must be sustained in order to install a new green plant

[6]For discussions about the monopolistic energy market assumption and the related strategies for market power exercise, please refer to Lamperti et al. (2018).

of vintage τ. Details are reported in the Appendix A.7.

The technologies of green and dirty plants change over time through innovation. The R&D expense by the electricity monopolist is a fraction $v_e \in (0,1)$ of previous period sales. The R&D budget is entirely employed for innovation purposes, as there are no competitors to imitate. Considering that total revenues ($S_e(t)$) are generated from both green and dirty energy sales, R&D investment in each technological trajectory is proportional to the revenues generated therein.

Innovation in the green technology, if successful, leads to lower fixed costs, thus encouraging the installation of green plants. A successful innovation in the dirty technology, instead, works through a better thermal efficiency and the abatement of greenhouse gas emissions. The details of the innovation process in the energy sector are described in Appendix A.8.

2.3 Climate change and global warming

A climate module is a necessary component of the modelling effort to relate climate change and the growth pattern of the simulated world in an endogenous way. To reconstruct this relation, as in Lamperti et al. (2018), the model borrows from a discrete-time version of the C-ROADS model of Sterman et al. (2012, 2013). Throughout the carbon cycle, the annual emissions from the consumption, capital, and energy sectors are used as inputs and later modelled the carbon exchanges between the atmosphere, the biomass and the oceans (details can be found in Appendix A.9). The underlying purpose of this part of the model is to avoid a complex and detailed description of the physical and chemical relations governing climate's evolution but, at the same time, to capture its major features paying particular attention to the inclusion of feedbacks that might give rise to non-linear dynamics.[7]

Global mean surface temperature is determined by the heat content of the surface and mixed layer of the oceans, which are aggregated into a single compartment. To model the behaviour of temperatures in the different layers, the DSK model builds on Schneider and Thompson (1981) and Nordhaus (1992). The heat content of the different layers is modulated by their reciprocal exchanges and, with respect to the upper compartment (atmosphere and surface oceans), by the CO_2 radiative forcing.[8] In particular,

$$T_m(t) = T_m(t-1) + c_1 \left\{ F_{CO_2}(t) - \lambda T_m(t-1) - c_3 [T_m(t-1) - T_d(t-1)] \right\} \tag{6}$$

$$T_d(t) = T_d(t-1) + c_4 \left\{ \sigma_{md} [T_m(t-1) - T_d(t-1)] \right\}, \tag{7}$$

[7] In this respect, the DSK model can be categorized in between so-called Simple Climate Models (Houghton et al., 1997, for a review) and Earth-system Models of Intermediate Complexity (for a review Claussen et al., 2002).

[8] Radiative forcing is a measure of the influence a factor has in altering the balance of incoming and outgoing energy in the Earth-atmosphere system and is an index of the importance of the factor as a potential climate change mechanism (IPCC, 2007). To simplify we use CO_2 as a proxy for all green house gases and we consider only its radiative forcing.

where T_i is the temperature in the different layers relative to pre-industrial levels, R_i is the thermal inertia, λ is a climate feedback parameter, F_{CO_2} represents the radiative forcing in the atmosphere from GHG (relative to pre-industrial levels) and σ_{md} is a transfer rate of water from the upper to lower oceans accounting also for the heat capacity of water. The main climate variable we are interested in is the temperature of the surface-upper oceans compartment, T_m. Accumulation of GHG leads to global warming through increasing radiative forcing according to a logarithmic relationship:

$$F_{CO_2}(t) = \gamma \log\left(\frac{C_a(t)}{C_a(0)}\right). \tag{8}$$

Equation (8) represents the main link between anthropogenic emissions, which contribute to increase the concentration of carbon in the atmosphere at any period, and climate change, which is induced by the radiative forcing of atmospheric GHGs.

2.4 Environmental Permits

We extend the DSK model by incorporating permits for climate-altering emissions. We start from the most defused permitting system for GHG, namely tradable permits. We consider two different institutional arrangements for emissions trading - first, keeping the number of permits fixed and then reducing it along the simulation time. Next, we study how emissions, climate, and the economy change if operational permits replace the emissions trading system, primarily used for other polluting emissions. The details on each type of environmental permit system are provided below.

2.4.1 Emissions trading system (ETS)

In our stylised tradable permits system, the simulation starts with the regulator distributing emissions certificates to firms, in an amount equal to the regulatory emissions limit (see the details on the ETS design in the review of Kanamura, 2021).[9] Accordingly, certificates received by a firm determine the individual emissions limit. If sectors in aggregate comply with the regulatory cap ($Em^s_{tot} \leq \bar{Em}^s$), then the price of certificates is 0 ($P^s = 0$), where Em^s_{tot} denotes the total emissions of the sectors, $\bar{Em}^s$ is the regulatory emissions limit for the sectors. Suppose the sectors in aggregate emit above the regulatory cap (i.e., $Em^s_{tot} > \bar{Em}^s$). In that case, the price of the certificate is positive ($P^s > 0$) and is determined as a function of net demand for certificates($P^s = f(\Theta)$) and is defined as follows:

$$P^s(t) = \begin{cases} p^s(t-1), & \text{if } \Theta(t) = 0 \\ p^s(t-1) - \iota * |\Theta(t)| * N_c^{-1}(t), & \text{if } \Theta(t) < 0, \\ p^s(t-1) + \iota * |\Theta(t)| * N_c^{-1}(t), & \text{if } \Theta(t) > 0 \end{cases} \tag{9}$$

[9] We have set up the regulatory emissions limit relying on the Thomson Reuters ASSET4 dataset, matching it with the scale of 3 industries in our model and calibrating it accordingly.

where $\Theta = D^s - S^s$ is the difference between the demand (D^s) and supply (S^s) of permits, $p^s(t-1)$ is the price of certificate in the previous period, $\iota > 0$ is a scaling parameter and N_c is the number of emission permits in the system. In the model, N_c takes two forms referring to two different institutional setups in the model. First, we fix the number of environmental permits in the ETS along the simulations (referring to ETS_F). Secondly, we allow the number of emission permits to decline along the simulations (referring to ETS_D). The latter evolves based on emission cap evaluation:

$$\bar{Em}^s(t) = \bar{Em}^s(t-1) - \Omega * \bar{Em}^s(0),$$

where $\bar{Em}^s(0)$ is the initial emission cap and $\Omega > 0$ is a linear reduction factor. We chose the Ω to match the pace of emissions cuts in EU ETS Revision for Phase 4[10], according to which the overall number of emission allowances will decline at an annual rate of 4.2% in the future.

Demand and supply for certificates are aggregated at the individual level and are represented by the following rules:

$$D^s(t) = \sum_i (Em_i(t) - \bar{Em}_i(t))^+$$

$$S^s(t) = \sum_i (Em_i(t) - \bar{Em}_i(t))^-,$$

where demand for certificates is the sum of the positive differences between the individual emissions and the regulatory emissions limit, while supply is the sum of the negative differences. The matching mechanism between the supply and demand of certificates is shown in Figure 2. Firms demanding permits (vertical block) and those supplying permits (horizontal block) are sorted in casual order. In this way, the first firm on the demand side is matched to all suppliers starting from the first one and then moving to the second, third, etc., until demand is not matched or the queue runs out of suppliers. Once the certificates demand of a firm is wholly or partially matched, the matching algorithm moves to the second firm in the demand queue, and the procedure is repeated.[11]

The dynamics of a carbon price is illustrated in Figure 3, for a given run of the simulation model. Let us first discuss the case for the ETS with the fixed number of carbon permits, which leads to almost a stationary carbon price, with several episodes when the carbon price is low, but different from 0 - i.e. cases wherein all three sectors (i.e., consumption-good, capital-good and energy sectors) almost complied, in the aggregate, with the sectoral emissions limits.[12] In case we reduce the emission permits with a constant reducing factor (Ω), we can notice an increasing dynamics of the carbon price, resulting in a costly ETS system targeting the general reduction of

[10]For further details about the Revision for Phase 4 in EU ETS system refer to the following link: `https://ec.europa.eu/commission/presscorner/detail/en/qanda_21_3542`.

[11]The matching algorithm in the ETS market is borrowed from Popoyan et al. (2020), where the matching procedure is applied in the interbank market.

[12]The fact that banking of certificates is not allowed in the model may lead prices to occasionally drop to zero. The EU-ETS carbon prices crashed in April 2006, after the release of the 2005 GHG emissions revealed the market to be over-allocated. After a temporary resurge, the price collapsed to near zero during 2007 (Hintermann, 2010). Another period wherein they declined and were persistently low was the year 2013. The evidence in Koch et al. (2014) suggests this might be related to interactions of the EU-ETS market with recessionary dynamics and the increasing deployment of renewable energy sources.

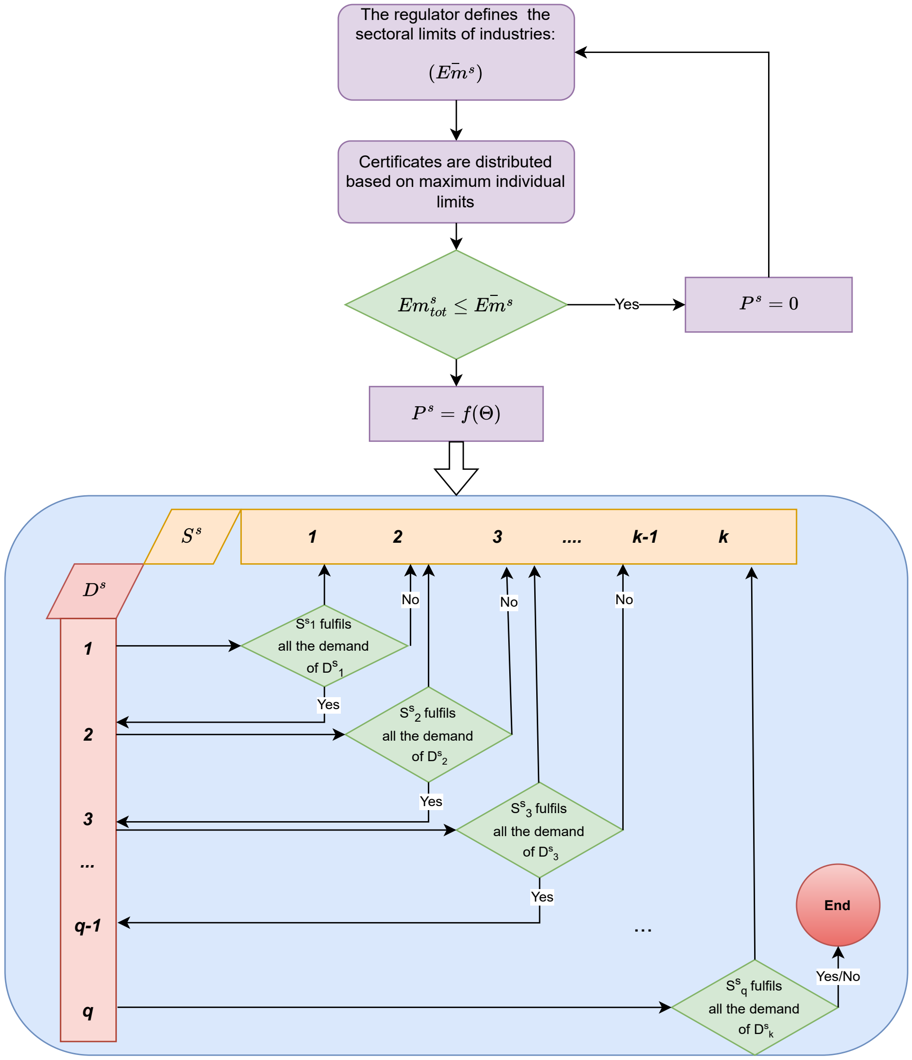

Figure 2: Decisions on permit trading system

carbon emission. The comparison of two ETS systems with different designs (i.e., a fixed number of permits vs a declining number of permits) is clear evidence of the impact of institutional factors on trading dynamics and its sensitivity towards its design.

It is worth mentioning that our simplified model of an ETS does not assume some real-world features of emissions trading, such as banking of certificates, floor prices, or carbon offsets.[13]

2.4.2 Operational permits

In the operational permit scenarios, firms can begin and continue production if they obtain a permit from the regulatory authority. Such operational permits are granted to firms whose emissions

[13] Related to carbon offsets, it is worth noting that the DSK is not a multi-country model, hence features such as carbon leakage and Sustainable Development Mechanisms are assumed away by construction. The same considerations apply to the carbon border adjustment mechanism included in the EU-ETS reform, approved in December 2022 (see `https://www.consilium.europa.eu/en/infographics/fit-for-55-eu-emissions-trading-system/`).

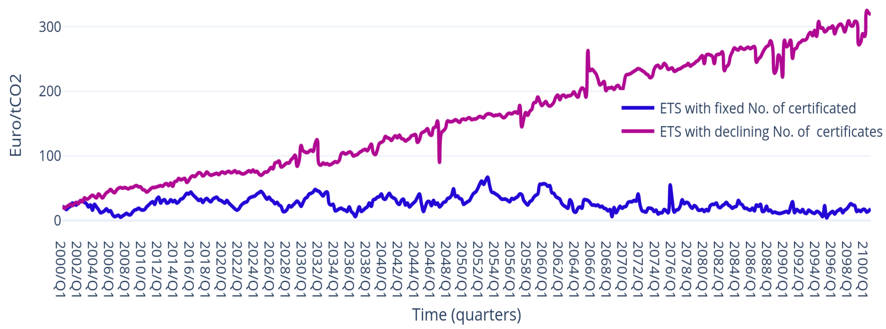

Figure 3: Dynamics of a carbon price (representative run) in an ETS with Fixed permits versus ETS with declining permits.

are below a regulatory limit, computed according to the best available technology (BAT). BAT in our model corresponds to the machineries characterised by the highest environmental friendliness.

We distinguish between centralised and decentralised permits. In a centralised operational permits system, only large firms (above a certain number of employees, namely 500) are monitored by the regulator; all firms need to respect the emissions limit in a decentralised operational permits system. Once operational permits are granted, emission limit violations are sanctioned through penalties.

In the first set of experiments, penalties are applied in every period when the emissions limits are violated. Penalties correspond to a share of the annual profits.[14] The penalty is calibrated to 4.1%, using the Thomson Reuters Asset4 ESG database.

In an additional scenario, firms violating emissions limits are required to implement *corrective measures* that allow reducing emissions below the limit within 3 quarters. After the 3-quarter period expires, penalties are applied if emission limits are still violated. This scenario was partly inspired by the transformation plans regulated by the revised IED as well as the provision of the US Clean Air Act that emission limit violators can be obliged to adopt "rectification or corrective measures".[15]

Corrective measures are assumed to be sector-specific. Corrective measures for capital good firms consist of an upgrade of the share of revenues invested in R&D for innovation, from ξ to $\xi + \zeta$

[14]Regulations about operational permits offer a wide array of penalties, such as a share of the firm turnover (8% of turnover in the revised IED, see Halleux (2022)); fines proportional to the violation and to the environmental damage (in the US Clean Air Act); revocation of tax breaks and exemptions. Our choice of a penalty on profits is similar to the latter type of penalty. It was also influenced by considerations concerning the dynamics of bankruptcies: simulations using penalties on turnover, indeed, display higher firm exit counts.

[15]According to Article 27d in the revised IED, *Operators would be required to produce installation-specific transformation plans by 30 June 2030 as part of their environmental management systems, or later, depending on the activities covered by Annex I that are involved. Such plans would detail how the installation would transform itself during the 2030-2050 period in order to contribute to the emergence of a sustainable, clean, circular, and climate-neutral economy by 2050.* In our model, corrective measures are required only for emissions limit violators.

(with $\zeta > 0$ and $\xi > 0$):

$$IN_i(t) = (\xi + \zeta)RD_i(t). \tag{10}$$

Similar corrective measures are assumed for the energy producer, which is required to increase its R&D on green technologies:

$$RD_{ge}(t) = (\xi + \zeta)S_{ge}(t-1). \tag{11}$$

With regards to the consumption good sector, corrective measures require a speed-up of machine replacement investments (said otherwise: less patient replacements), pushing firms to search machines that are more environmentally friendly: $\frac{p^{new}}{c_j^{con}(t)-c^{new}} \leqslant b - \delta$, with $0 < \delta < b$, p^{new} and c^{new} being the price and unit cost of production associated to a new machine.

While sector-dependent, corrective measures modelled here imply firm-specific costs, since firms violating emission limits differ in terms of machine vintages and R&D budgets.

Figure 4 sheds light on how the operational permitting process is modelled. We consider (i) penalties every period (1st diagram in Figure 4) and (ii) operational permits with corrective measures.[16]

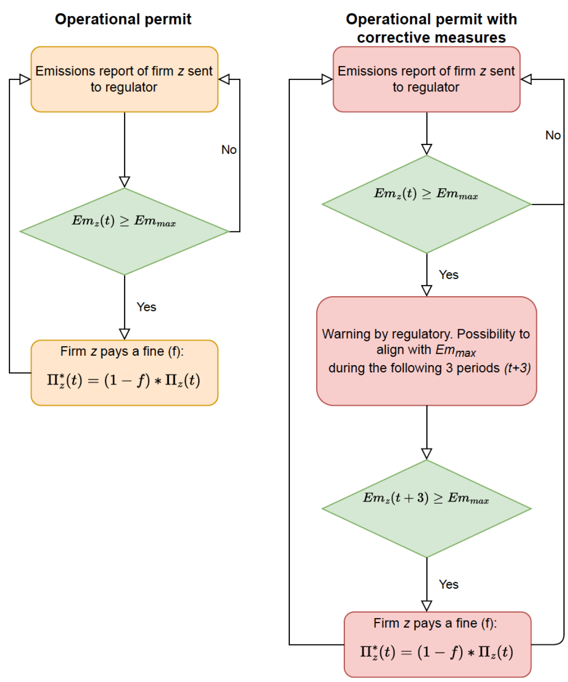

Figure 4: Decisions on environmental penalties.
Note: Simple operational permit on the *left* and operational permits with corrective measures on the *right*

[16] As an alternative we also consider a scenario with a fraud where a share of firms (10% in each industry) communicates false data regarding its emissions level. The results of this experiment can be obtained upon request.

3 Simulation results and policy experiments

Considering the non-linearities ingrained in most agents' decision rules and the interaction complexity among them, finding an analytical closed-form solution to the model is not feasible. Accordingly, we perform an extensive Monte Carlo analysis to wash away across-simulations variability and to study the properties of the stochastic processes driving the co-evolution of micro-and macro-economic variables. We run the model for 100 Monte Carlo iterations across either 400 or 600 time periods that should be taken as quarters, accordingly obtaining projections for variables until the year 2100 (commonly used as a reference point for integrated assessment models) or 2150.

3.1 Empirical validation

Using the best practice in the ABM literature, the baseline setup model should be empirically validated before claiming that it can be used as a policy laboratory. As a baseline configuration of the model, we consider the business-as-usual scenario (BAU), wherein climate damages are absent and no climate policies are in place. The baseline setup will then be compared to the results of different experiments to reveal whether operating permits or carbon trading provide better macro/micro and climate outcomes.

In line with the prevailing practice in the macro ABM literature (see Fagiolo and Roventini, 2012; Roventini and Fagiolo, 2017), the model is calibrated using indirect calibration techniques (Windrum et al., 2007). In this, the model parameters, reported in Table 9 in Appendix B, are chosen to match stylised facts. Table 1 reports the main empirical stylised facts the model can replicate along with their scholarly references. In this section, we focus on the most central ones while leaving the rest available upon request.

Stylized Facts	**Empirical Studies**
Macro-economic stylized facts	
(SF1) Endogenous self-sustained growth	Burns and Mitchell (1946), Stock and Watson (1999)
(SF2) Fat-tailed GDP growth-rate distribution	Fagiolo et al. (2008), Castaldi and Dosi (2009)
(SF3) Recession duration exponentially distributed	Ausloos et al. (2004), Wright (2005)
(SF4) Relative volatility of GDP, consumption and investments	Stock and Watson (1999), Napoletano et al. (2006)
(SF5) Cross-correlations of macro-variables	Stock and Watson (1999), Napoletano et al. (2006)
(SF6) Pro-cyclical aggregate R&D investment	Walde and Woitek (2004)
(SF7) Cross-correlations of credit-related variables	Foos et al. (2010), Mendoza and Terrones (2012)
(SF8) Pro-cyclical energy demand	Moosa (2000)
(SF9) Synchronization of emissions dynamics and BS	Peters et al. (2012), Doda (2014)
(SF10) Co-integration of output, energy demand and emissions	Triacca (2001), Ozturk (2010), Attanasio et al. (2012)
(SF11) Medium-term fluctuations vs. classical economic BS	Gertler & Comin, 2006
Microeconomic stylized facts	
(SF12) Firm (log) size distribution is right-skewed	Dosi (2007)
(SF13) Fat-tailed firm growth-rate distribution	Bottazzi and Secchi (2003, 2006)
(SF14) Productivity heterogeneity across firms	Bartelsman and Doms (2000), Dosi (2007)
(SF15) Persistent productivity differential across firms	Bartelsman and Doms (2000), Dosi (2007)
(SF16) Lumpy investment rates at firm level	Doms and Dunne (1998)
(SF17) Persistent energy and carbon efficiency	DeCanio and Watkins (1998), Petrick et al. (2013)

Table 1: Stylised facts replicated by the model

We first examine the ability of the model to replicate the stylised facts about macroeconomic aggregates. Referring to the first stylised fact (SF1) in Table 1, the Figure 5 on the left shows that the model is capable to robustly generating endogenous self-sustained growth rates with persistent fluctuations. Moreover, zooming-in at business cycle frequencies (see Figure 5), bandpass-filtered GDP, investment, and consumption series (Baxter and King, 1999) reveal the familiar "rollercoaster" dynamics as observed in real-world time series (Stock and Watson, 1999; Napoletano et al., 2006).

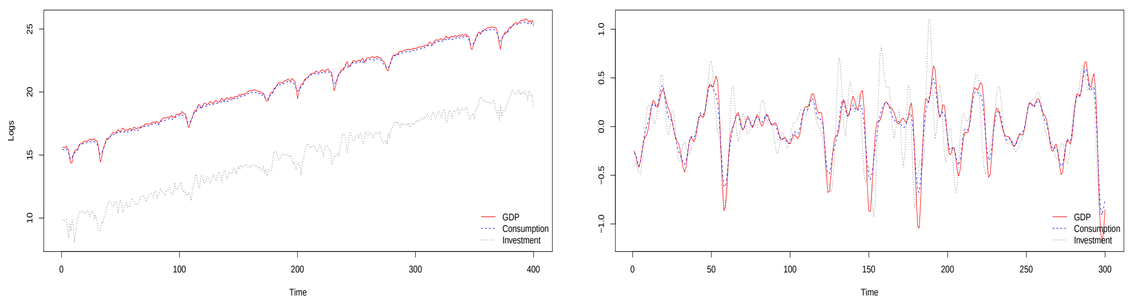

Figure 5: Level of GDP, consumption and investment (*left*) and bandpass-filtered GDP, investment, and consumption (*right*)

As found in the empirical literature, GDP, consumption, and investment display strictly positive average growth rates (cf. Table 2). Performing Dickey-Fuller tests, they also seem to exhibit a unit root. We compute standard deviations of output and the other bandpass filtered series on our way of exploring the business cycle frequencies. In line with the empirical literature (Stock and Watson, 1999), our model confirms that investment is more volatile than GDP, whereas consumption is less volatile.

	GDP	Consumption	Investment
Avg. growth rate	0.0268	0.0250	0.0248
	(0.0002)	(0.0002)	(0.0003)
Dickey-Fuller test (logs)	-0.1867	-0.1542	-0.9109
	(0.0673)	(0.0756)	(0.0379)
Dickey-Fuller test (Bpf)	-2.7282	-3.1599	-3.9568
	(0.1102)	(0.0404)	(0.0337)
Std. dev. (Bpf)	0.1402	0.1320	0.3916
	(0.0012)	(0.0010)	(0.0084)
Rel. std. dev. (GDP)	1.0000	0.9429	2.8007

Table 2: Output, investment, and consumption statistics.
Notes: Bandpass-filtered (6, 32,12) series. Monte-Carlo simulation standard errors in parentheses.

Our investigation on the stylised facts at business cycle frequencies continues with the computation of cross-correlations structure between GDP and the other macro series (SF5). In tune with the empirical literature (Stock and Watson, 1999), also in our model, consumption and investment are pro-cyclical, with inflation showing milder pro-cyclicality, while unemployment and prices are countercyclical (see Figure 6).

All in all, the simulation results show that our model is able to track the empirical evolution of a variety of macro measures along with climate-related ones, such as emissions growth rates and energy consumption (see Figure 7). Additionally, energy demand displays a lagging and pro-

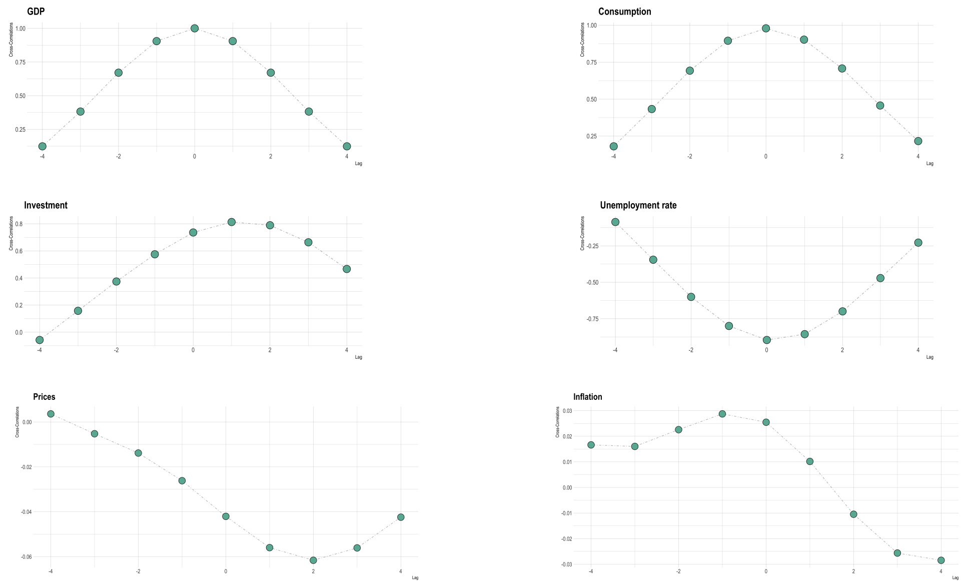

Figure 6: Cross-correlations between output and main macro-economic aggregates.
Note: Bandpass-filtered (6, 32, 12) series. Average cross-correlations from a Monte Carlo of size 100.

cyclical pattern (see Figure 8) in line with the empirical evidence in Moosa (2000), confirming that industrial production causes energy use at business cycle frequencies (Thoma, 2004).

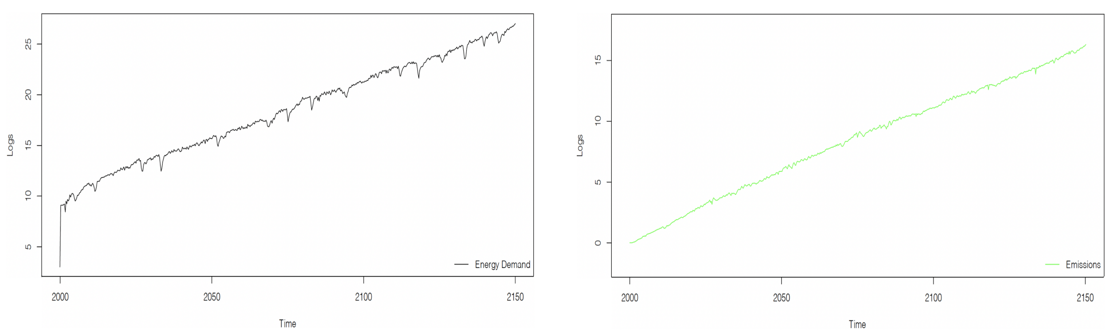

Figure 7: Emissions and energy demand dynamics
Note: The figures are in log-scale. The emissions are expressed in GtC and the energy demand is in GWh.

Finally, we have assessed the model's ability to reproduce the stylised facts about firm-level investment patterns. The model is indeed able to generate, as an emergent property, investment lumpiness (Caballero, 1999). Indeed, in each time step, consumption-good firms with "near" zero investment co-exist with firms experiencing investment spikes (see Figure 9 and relate it to Gourio and Kashyap (2007)).

Finally, we refer to another famous stylised fact mainly put forward by Comin and Gertler (2006). They claim that the medium-term fluctuations - between 33 and 120 quarters - are larger than those of the classical economic business cycles. There is extensive literature showing that

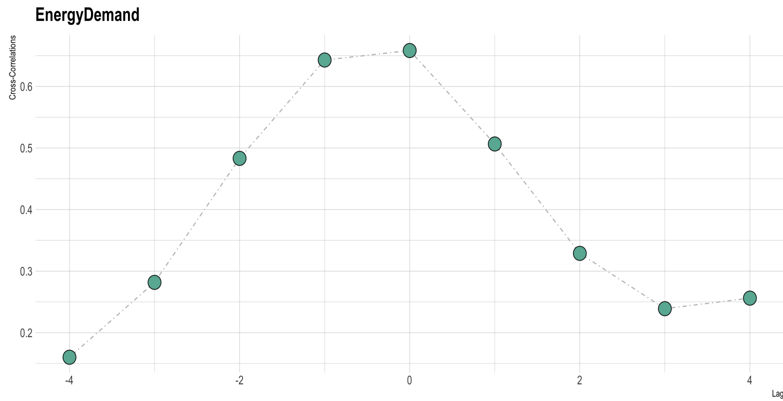

Figure 8: Cross-correlations between output and energy demand.
Note: Bandpass-filtered (6, 32, 12) series. Average cross-correlations from a Monte Carlo of size 100.

these cycles are related to R&D, and it is a way of saying that short-term crises have long-term effects. Hereby we show in Figure 10 that such fluctuations are wider and have larger dispersion than the standard business economic cycle. In this case, the GDP is indeed significantly correlated with R&D expenditures for the capital good sector.

3.2 Simulation Results

Having our model empirically validated, we can now explore and compare the macroeconomic, microeconomic, and climate outcomes in scenarios characterised by different environmental permit systems. Macroeconomic results are displayed below, whereas microeconomic and climate outcomes are reported and commented on later on in the section. The last part of the section is enriched with a sensitivity analysis of mail policy design variables.

Macroeconomic performance: We now explore the impact of differently designed environmental permit systems (emission trading vs individual operational permits) on a range of macroeconomic variables. Among those, we consider the growth rate of output, investments, and energy demand, as well as the rate of unemployment. We compare these alternative scenarios with the business as usual to better grasp the impact of the policy. The results of the experiments are reported in Table 3.

We focus first on emissions trading system (ETS) scenarios: emissions trading with a declining number of permits and hence high compliance cost (ETS_D), and emissions trading with a fixed number of permits (i.e., low compliance cost - ETS_F). The first three rows of Table 3 allow us to compare macroeconomic outcomes under the BAU scenario and the two ETS scenarios. The emissions trading scheme has an apparently positive effect on macro-dynamics, specifically if we consider the ETS with a declining number of permits, while outcomes in the low-cost emission trading system (i.e., ETS_F) do not depart from those of the BAU scenario.

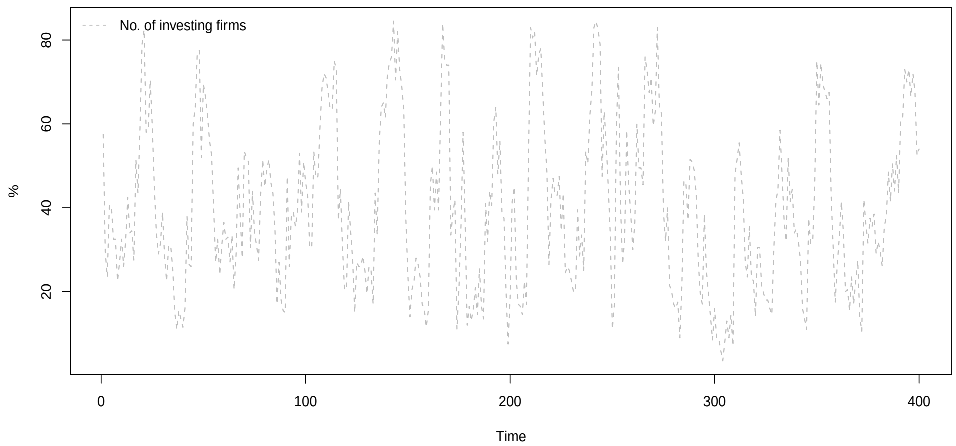

Figure 9: Investment lumpiness

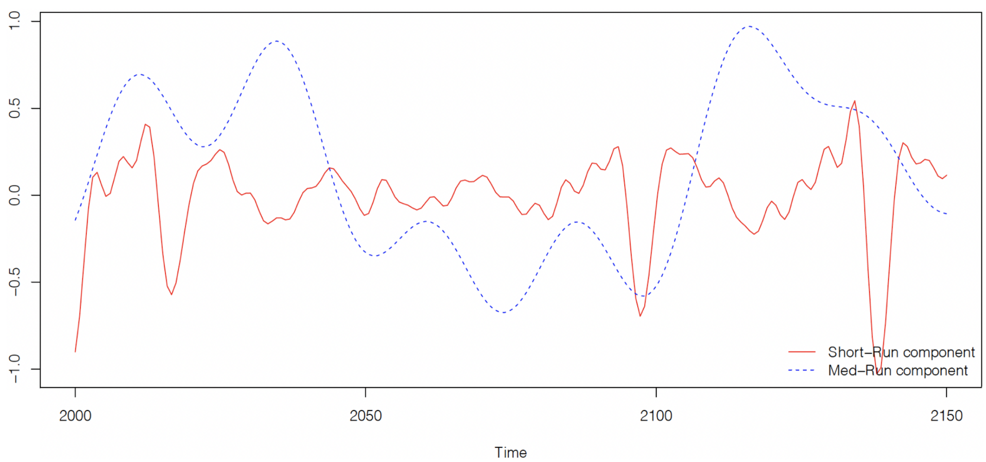

Figure 10: Short-run and medium-run components of GDP

Next, we explore operating permits scenarios: decentralised and centralised permits required only on capital-good firms (D_{Cap}, C_{Cap}); decentralised and centralised permits required only on consumption-good firms (D_{Cons}, C_{Cons}); centralised permits required on the energy monopolist (C_{Energy}); decentralised and centralised permits required on all firms (D_{All}, C_{All}) and $CorrM$ centralized permits with the adaptation period and corrective measures. According to the lower rows of Table 3, decentralised permits negatively affect macro-dynamics in respect to the BAU scenario, and this occurs when only firms in a given sector are required to obtain permits (either D_{Cap} or D_{Cons}), as well as when permits are mandatory in all sectors (D_{All}). Instead, centralised permits exercise marginally positive effects, with magnitudes changing across scenarios. Suppose we insert in the horserace the centralized permits in all the sectors with corrective measures ($CorrM$). In that case, it is clear that in the operational permits scenarios, the $CorrM$ is the first best in terms of macroeconomic performance. We can also notice that while comparing the two best performances from 2 differently designed permit scenarios, namely the ETS_D and $CorrM$, they closely follow each other.

	GDP G.	**Investments G.**	**Unemployment**	**Energy Demand G.**
BAU	0.0268	0.0248	0.1090	0.0244
	(0.0062)	(0.0027)	(0.0159)	(0.0025)
		Emission Trading systems (ETS)		
ETS_F	0.0226	0.0215	0.1157	0.0227
	(0.0045)	(0.0026)	(0.0171)	(0.0039)
ETS_D	0.0318	0.0275	0.0893	0.0238
	(0.0033)	(0.0023)	(0.0132)	(0.0031)
		Operational Permits		
$CorrM$	0.0316	0.0269	0.0947	0.0219
	(0.0037)	(0.0028)	(0.0182)	(0.0034)
D_{Cap}	0.0182	0.0140	0.1607	0.03435
	(0.0068)	(0.0024)	(0.0175)	(0.0025)
C_{Cap}	0.0209	0.0190	0.1424	0.0299
	(0.0069)	(0.0028)	(0.0172)	(0.0031)
D_{Cons}	0.0193	0.0121	0.1458	0.0236
	(0.0020)	(0.0102)	(0.0142)	(0.0051)
C_{Cons}	0.0261	0.0240	0.0924	0.0217
	(0.0020)	(0.0020)	(0.0131)	(0.0056)
C_{Energy}	0.0184	0.0194	0.2334	0.0216
	(0.0032)	(0.0025)	(0.0133)	(0.0032)
D_{All}	0.0131	0.0178	0.2681	0.0226
	(0.0019)	(0.0175)	(0.0123)	(0.0062)
C_{All}	0.0291	0.0247	0.0872	0.0264
	(0.0021)	(0.0034)	(0.0135)	(0.0055)

Table 3: Economic performances under heterogeneous environmental permit scenarios. Monte Carlo standard deviations in parentheses.
Note: All values refer to a Monte Carlo of size 100. BAU - business-as-usual scenario considered as baseline, ETS_F - ETS with fixed number of permits; ETS_D - ETS with declining number of permits; $CorrM$ - centralized permits with corrective measures; D_{Cap} - decentralised permits applied only to capital good firms; C_{Cap} - centralised permits applied only to capital good firms; D_{Cons} - decentralised permits applied only to consumption good firms; C_{Cons} - centralised permits applied only to consumption good firms; C_{Energy} - centralised permits applied only to energy producing firm; D_{All} - decentralised permits applied to all sectors; C_{All} - centralised permits applied to all sectors.

As a second round of macro experiments, we compare economic performances in terms of GDP growth, the likelihood of an economic crisis, unemployment rate, and emission growth in time slices across 150 years (see Figure 11) to see the evolution of it across time. The figure features the BAU scenario, the ETS with a declining number ($ETS-D$) and fixed number ($ETS-F$) of permits, and the operational permit scenarios, with and without corrective measures. One can notice two clear clusters of results. In the first cluster, we find the centralized operational permits with corrective measures (orange line) together with an ETS permit system with declining permits (green line) performing similarly and pointing in the same direction. In the second cluster, we find business as usual (dark blue line), centralized (red line) and decentralized permits (grey line) together with $ETS-F$ with a trading system with a lower cost of compliance (light blue) performing worse and lagging behind the first cluster. In line with the results in Table 3, the temporal analysis shows that compared to centralized permits and to the BAU scenario, decentralized permits perform poorly in macroeconomic terms resulting in lower economic growth, higher rate of unemployment, likelihood of economic crisis and emission growth, while the ETS with declining permits is mainly leading the race (even if not always and not in all the indicators), leaving the operational permits system with corrective measures as the second best. Consistently with the other macro indicators in Table

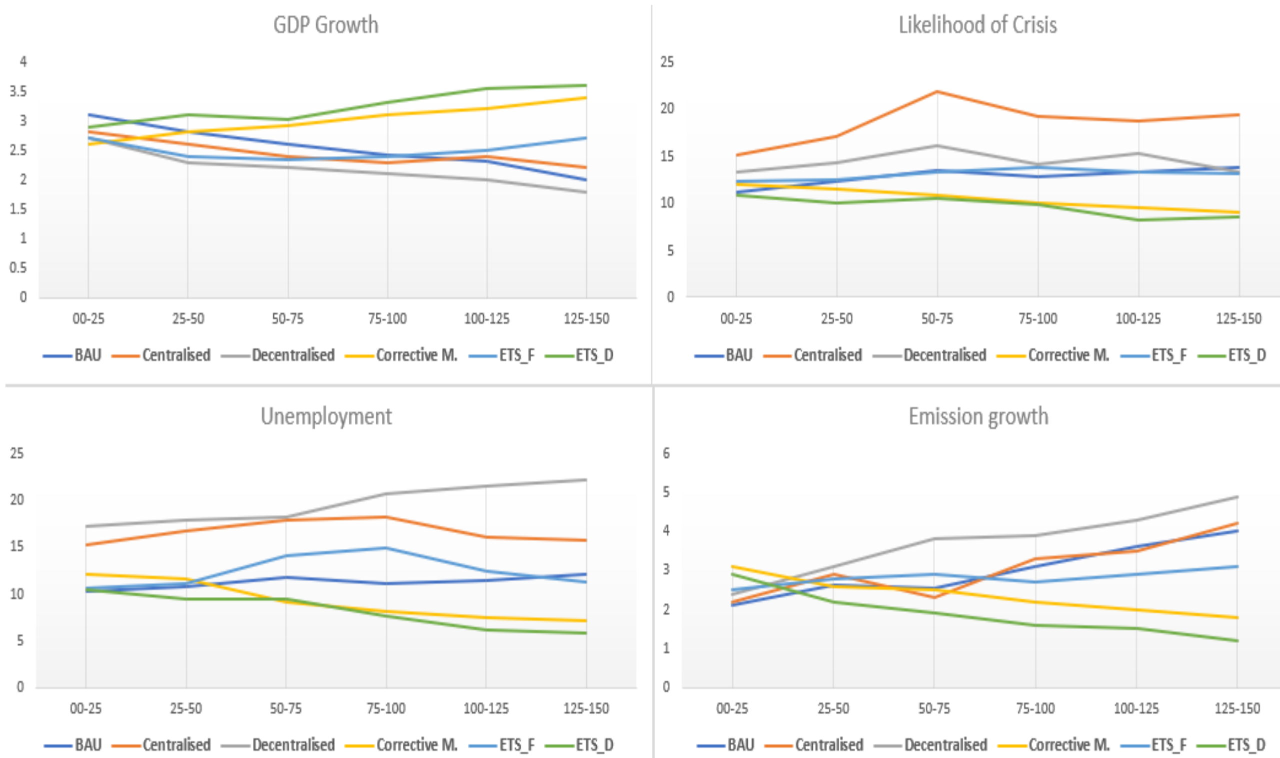

Figure 11: Impact of different permit systems on macroeconomic variables
Note: BAU - business-as-usual scenario (BAU); *Centralised* - centralised operational permits for all sectors; *Decentralised* - decentralised operational permits for all sectors; *Corrective. M.* - centralised permits of all firms with corrective measures; *ETS-F* - Emissions trading system with a fixed number of permits; *ETS-D* - Emissions trading system with a declining number of permits. All panels refer to a Monte Carlo of size 100.

3, emissions trading schemes with a fixed number of permits perform relatively close to the BAU scenario.

Microeconomic dynamics: In this part of the paper, we tried to determine the mechanisms generating our macro results above. In particular, we want to find out what is causing the worst performance of decentralized individual operational permits against the centralized ones. To understand what are the microeconomic drivers of such dynamics, we looked at the failure (mortality) rates of the firms in different sectors. Such analysis is illustrated through violin plots in Figure 12 indicating the corresponding distribution of failure rates in capital- and consumption-good industries. Plots combine a boxplot and a kernel density figure, with the centralised permits scenarios in green and decentralised ones in violet. Under emissions trading schemes (the single violin in the plot) simulations reveal a relatively low firm failure rate both for consumption- and capital-good industries. When all the firms are regulated with decentralised operational permits, without corrective measures, in the capital- and consumption-good industries, the failure rate is higher than in the centralised case. Evidently, in the model, the mortality rates of firms are driven by the penalties. In the absence of corrective measures, firms that exceed the emissions limits may fail because the fines are too costly. Accordingly, we find higher unemployment rates, lower GDP, investment, and energy demand in decentralised operating permit scenarios (see Table 3, for details).

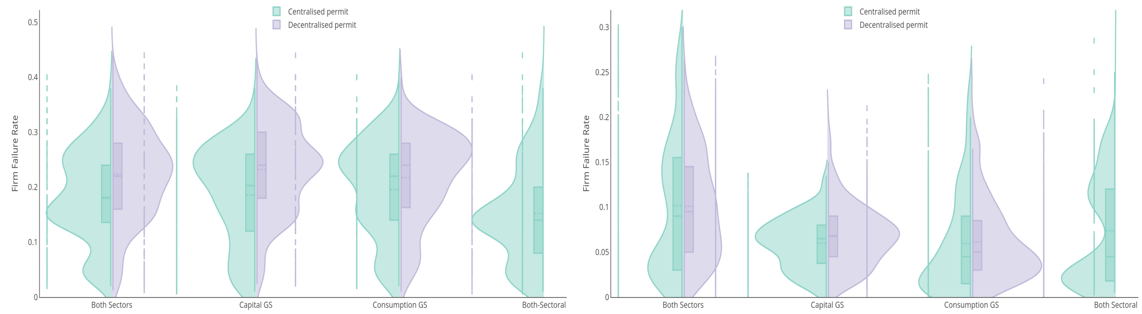

Figure 12: Mortality rates of capital-good *(left)* and consumption-good *(right)* firms in different permit scenarios

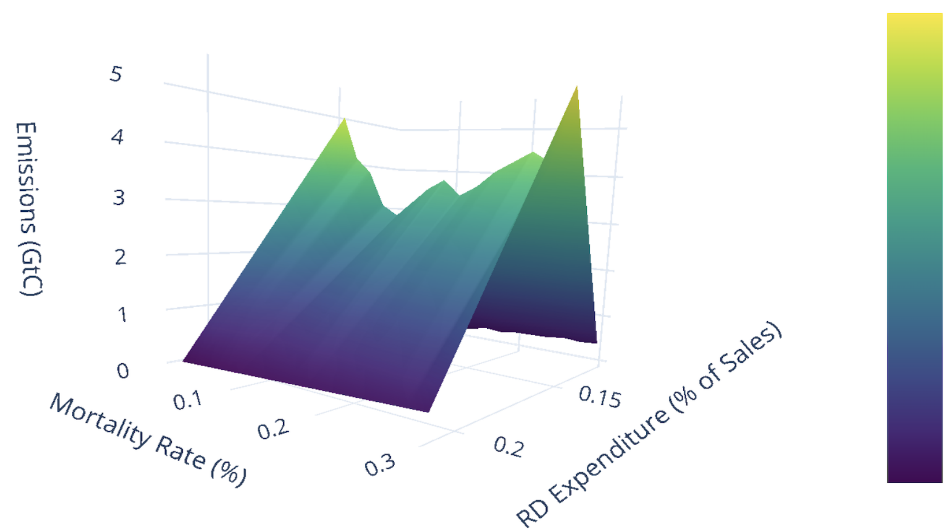

Figure 13: R&D expenditures, emissions and mortality rate of firms

On the other hand, even when corrective measures are assumed, attempts to contain emission levels within the regulatory limits may not succeed. In this respect, we explored the connection between R&D investments, mortality rates, and emission levels. This threefold connection is depicted in Figure 13. As one can note from the 3D surface, increasing R&D expenses results in a positive impact on emissions only until a certain point. When the R&D investment share is large enough, and the firm is not succeeding in finding technology to mitigate emissions, both the emissions and firm exit rates increase. Still, the relatively good performance of an operational permit system with corrective measures is suggesting that the costs of implementing such plans are worth bearing, in light of the technological improvements induced by the corrective measures.

In addition to the above results, we found an interesting impact of the permit system regime on firm size. As a proxy for firm size, we use the year-standardised firm sales following Bottazzi

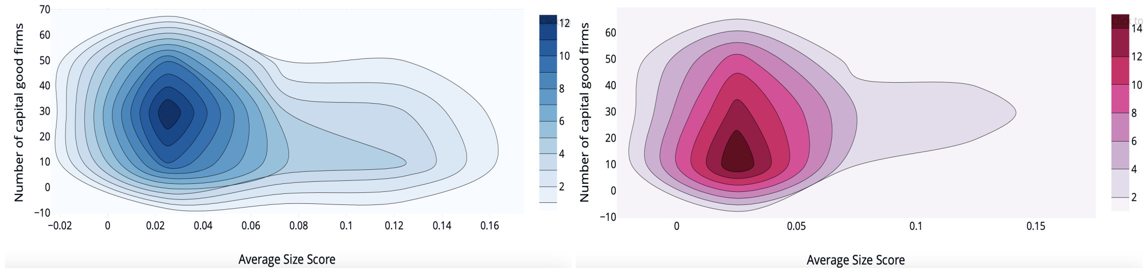

Figure 14: Distribution of size scores with Kernel density estimates
Note: The *left* panel indicated the distribution of size scores of BAU while *right* panel is responsible for centralised permits with corrective measures

and Secchi (2006); Dosi et al. (2010). Figure 14 shows the statistical distribution of the indicators of firm size scores. On the left panel is the BAU scenario and on the right panel is a centralised permit system with corrective measures. One can notice that the BAU case highlights a higher frequency of large firms, while in the right panel, large firms are less present. Such results tell us that in the centralised scenario, some large firms, that are under the regulatory lens, may shrink because it is costly to align with regulatory requirements.

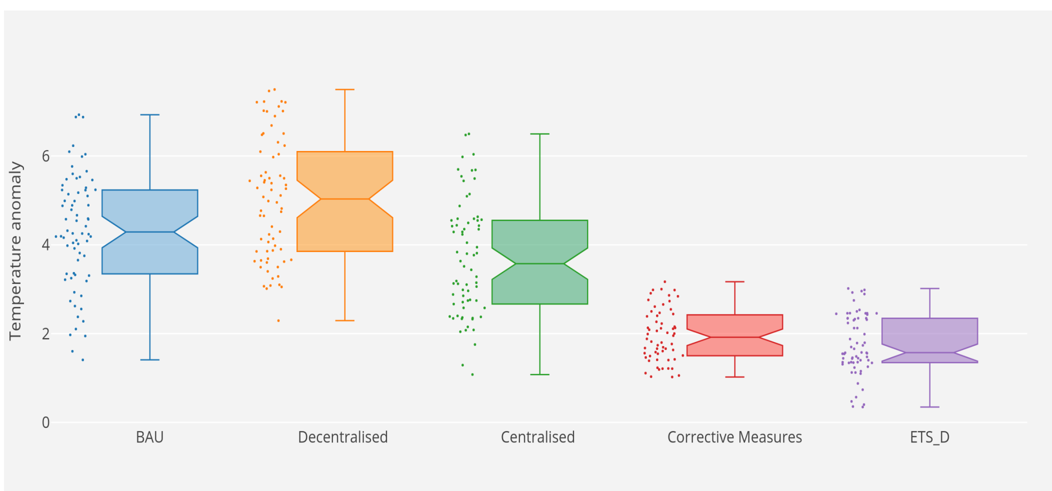

Figure 15: Distribution of temperature in different scenarios

Climate impacts: After exploring the impact of different environmental permit systems on both macro- and microeconomic variables, we explore the impacts on climate indicators. In particular, we look at the distribution of temperature anomalies expressed in Celsius degrees above the pre-industrial level. We show it in terms of a box-plot in Figure 15 referring to their minimum, maximum, and median values, as well as 1st and 3rd quartiles. In line with what was found previously, when looking on operational permit scenarios, we can see that centralised permits with corrective measures on an average yield the lowest temperature anomalies with respect to BAU and other scenarios, while decentralised permits yield the worst outcome. The emissions trading scheme with a declining number of permits performs best and yields the lowest average temperature anomaly, leaving the operating permits with corrective measures as the second best with only 0.23C° difference.

	BAU	**Decentr.**	**Central.**	**Correct. M.**	ETS_D	ETS_F
Energy demand growth	0.024	0.021	0.025	0.032	0.034	0.029
	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)
Volatility of energy demand	0.223	0.314	0.237	0.198	0.207	0.223
	(0.044)	(0.068)	(0.053)	(0.034)	(0.045)	(0.045)
Emissions at 2100	25.854	28.452	22.791	20.436	19.032	22.804
	(7.235)	(8.842)	(7.034)	(6.706)	(7.154)	(7.836)
Emissions growth	0.029	0.028	0.023	0.019	0.018	0.022
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)
Emissions volatility	0.322	0.362	0.312	0.303	0.272	0.304
	(0.027)	(0.034)	(0.021)	(0.019)	(0.027)	(0.023)
Share of green energy	0.324	0.291	0.347	0.401	0.426	0.356
	(0.263)	(0.227)	(0.294)	(0.312)	(0.276)	(0.304)
Temperature anomaly at 2100	4.27	5.03	3.57	1.90	1.67	2.55
	(0.513)	(0.542)	(0.424)	(0.304)	(0.471)	(0.483)

Table 4: Impact of different environmental permits systems on selected climate variables
Note: All values refer to a Monte Carlo of size 100. Emissions are expressed in GtC, which can be converted in $GtCO_2$ using the following conversion factor: 1 GtC = 3.67 $GtCO_2$. Temperature is expressed in Celsius degrees above the pre-industrial level, which is assumed to be 14°C.

Elaborating more on climate statistics, we introduce some selected climate variables across different environmental permit scenarios in Table 4. Numbers reported in the table are Monte Carlo averages across 100 years, with Monte Carlo standard errors in parentheses. Continuing the line of results we saw, we find that climate statistics and the share of green energy perform more favourably under an ETS with a declining number of permits, although an operating permit system with corrective measures is only slightly behind. Operational permit systems without corrective measures, and in particular the decentralised ones, are again leading to worse performances.

	Likelihood of the green transition in the BAU scenario.			
	Carbon intensive lock-in		Transition to green	
	84%		16%	
	Before 2025	After 2025	Before 2075	After 2075
	91%	9%	92%	8%
Output growth	2.714%	2.563%	3.127%	2.871%
	(0.002)	(0.001)	(0.004)	(0.002)
Unemployment	11.624%	12.452%	9.267%	10.125%
	(0.017)	(0.023)	(0.021)	(0.014)
Emissions at 2100	27.324	30.123	17.466	21.362
	(1.852)	(2.348)	(1.649)	(2.143)
Emissions growth	1.360%	1.484%	0.863%	0.947%
	(0.001)	(0.002)	(0.001)	(0.001)
Temperature at 2100	4.611	5.023	1.942	2.415
	(0.132)	(0.187)	(0.145)	(0.167)

Table 5: Likelihood of the green transition in the BAU scenario.
Note: All values refer to the average computed on the sub-sample of runs from a Monte Carlo of size 100. Standard errors are reported in parenthesis.

To better understand the impacts of environmental permit systems vis-à-vis the BAU scenario, we measure the frequency with which the economy undergoes a green transition (100% energy generated by "clean" sources) or falls in a carbon lock-in (100% energy generated by "dirty" sources). Following the methodology reported in Lamperti et al. (2020), Tables 5, 6, 7 and 8 report the

	Likelihood of the green transition in an operational permits system with corrective measures.			
	Carbon intensive lock-in		Transition to green	
	74%		26%	
	Before 2025	After 2025	Before 2075	After 2075
	89%	11%	91%	9%
Output growth	3.027	2.926	3.354	3.132
	(0.003)	(0.001)	(0.004)	(0.002)
Unemployment	10.013	11.872	8.763	9.423
	(0.018)	(0.022)	(0.014)	(0.15)
Emissions at 2100	22.154	26.045	14.306	17.354
	(1.423)	(1.602)	(1.078)	(1.129)
Emissions growth	1.173	1.247	0.647	0.803
	(0.003)	(0.001)	(0.002)	(0.001)
Temperature at 2100	3.264	3.807	1.745	1.956
	(0.154)	(0.172)	(0.118)	(0.137)

Table 6: Likelihood of the green transition in an operational permits system with corrective measures.
Note: All values refer to the average computed on the sub-sample of runs from a Monte Carlo of size 100. Standard errors are reported in parenthesis.

	Likelihood of transition in ETS with declining permits.			
	Carbon intensive lock-in		Transition to green	
	71%		29%	
	Before 2025	After 2025	Before 2075	After 2075
	82%	18%	87%	13%
Output growth	3.317	3.015	3.602	3.304
	(0.004)	(0.002)	(0.003)	(0.002)
Unemployment	9.524	10.021	7.746	8.173
	(0.032)	(0.036)	(0.024)	(0.015)
Emissions at 2100	19.736	22.153	13.451	17.024
	(1.809)	(1.791)	(1.021)	(0.921)
Emissions growth	1.061	1.102	0.498	0.602
	(0.002)	(0.001)	(0.001)	(0.002)
Temperature at 2100	2.527	2.915	1.382	1.638
	(0.154)	(0.183)	(0.094)	(0.104)

Table 7: Likelihood of transition in ETS with declining number of permits.
Note: All values refer to the average computed on the sub-sample of runs from a Monte Carlo of size 100. Standard errors are reported in parenthesis.

	Likelihood of transition in ETS with fixed permits.			
	Carbon intensive lock-in		Transition to green	
	78%		22%	
	Before 2025	After 2025	Before 2075	After 2075
	90%	10%	92%	8%
Output growth	2.814	2.602	3.186	2.961
	(0.003)	(0.002)	(0.004)	(0.004)
Unemployment	10.864	11.644	8.643	9.661
	(0.018)	(0.022)	(0.017)	(0.014)
Emissions at 2100	24.161	26.316	15.437	18.091
	(1.632)	(1.702)	(1.511)	(1.714)
Emissions growth	1.282	1.303	0.822	0.916
	(0.001)	(0.002)	(0.002)	(0.003)
Temperature at 2100	4.102	4.861	1.842	2.013
	(0.121)	(0.164)	(0.141)	(0.156)

Table 8: Likelihood of transition in ETS with fixed number of permits.
Note: All values refer to the average computed on the sub-sample of runs from a Monte Carlo of size 100. Standard errors are reported in parenthesis.

Monte Carlo averages of output growth, unemployment, emission growth, emissions, and temperature at 2100, along with their standard deviations for BAU and centralised permits with corrective measures, declining and fixed number permit ETS respectively. Next, we cluster runs based on the years needed to reach their statistical equilibrium state.

While in the BAU scenario, the likelihood of transition is 16%, the probability of a green transition in an ETS with declining permits the probability is 29% (Table 7), whereas it is 22% in a fixed number permit ETS (22%). ETS is not necessarily performing better than operational permits, which implies a 26% transition probability if corrective measures are imposed on firms, once more highlighting the importance of institutional design in the environmental permit system.

Sensitivity Analysis: We have tested the model sensitivity to the inserted policy design parameters, dividing the experiments into two parts. For the individual operational permit scenarios (i.e., centralised, decentralised, and permits with corrective measures), we have increased the penalty rate charged on firms' profits in case of non-compliance. We monitor how temperature anomalies change and record the result of the heatmap in Figure 16.

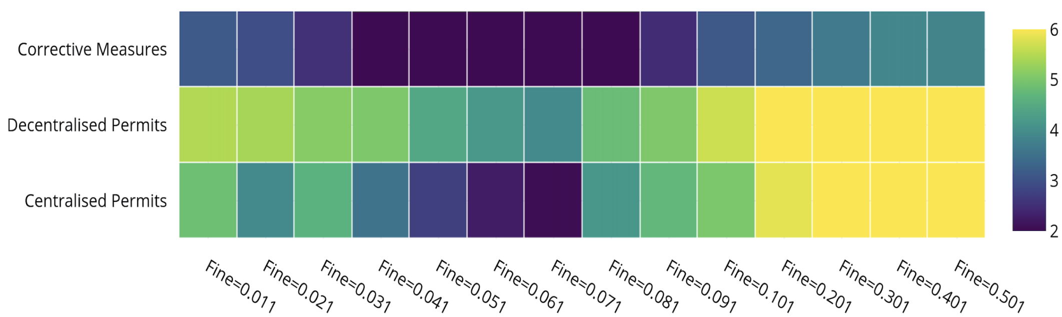

Figure 16: Temperature anomalies in different permit scenarios and penalty levels

We notice that our calibrated value for the penalty (i.e., 4.1% of firm profits) perhaps is not the best, and there is still room for a better policy design by setting it higher. The best outcomes are found for a penalty of around 7.1%. Clearly, if the fine level is too high, 40% or 50% as visible in the right-hand sign, average temperature anomalies with respect to pre-industrial levels become drastically higher. The transmission mechanism of this result is similar to what we observe in Figure 13 - the higher cost of regulatory incompliance negatively impacts the mortality rate of the firms, the production volumes, and the technology chosen, boiling down to higher emission levels and temperatures.

Next, we check how sensitive is ETS to the yearly linear reduction factor [17] upon which the number of environmental permits gets reduced in the system. We compare the temperature anomalies for the ETS system with a fixed number of permits (ETS_F), where the reduction factor is not applied, and ETS with a reduced number of permits (ETS_D) where increase the reduction factor applied from 1.2% to 14.2% on yearly bases. We find this experiment very useful, considering the revisions in the EU ETS system, where to reach environmental targets, the European Commission

[17] Considering the quarterly frequency of the model, the yearly reduction factor we have adopted from the data (4.2%) in the Table of parameters in Appendix B is transformed to a quarterly reduction factor by dividing it to 4. For the comparability to real scenarios, in Figure 17 we report on a yearly scale.

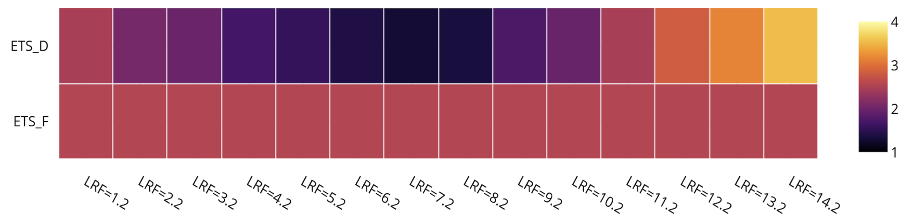

Figure 17: Temperature anomalies in different ETS permit systems with different linear reduction factor (LRF).
Note:ETS_D stands for the ETS system with a declining number of permits and ETS_F features ETS permits system with a fixed number of permits.

proposed a steeper annual emissions reduction of 4.2% instead of 2.2% per year under the current system. The results are reported in Figure 17 and evidence about a certain saturation point around 7.2% yearly reduction, meaning that the emission reduction factor can be increased further resulting in fewer permits for better results, but it cannot be increased forever, since the excessive demand over supply of the permits results in a massive failure in different markets. It is worth mentioning that the speed of emission permit reduction can also matter for market adaptation.

4 Conclusions

The paper has presented a new version of the Dystopian Schumpeter meeting Keynes (DSK) model by Lamperti et al. (2018), an agent-based integrated assessment model, to simulate the climate-economy co-evolution under different systems of emission permits. Along with its core Schumpeterian and Keynesian engines, the DSK model includes an energy sector with clean and dirty sources along with a climate box, and is able to replicate a wide ensemble of macroeconomic and climatic stylised facts.

Through model simulations, we assess the impact of an emissions trading system, the most commonly used permitting system in the realm of climate policy, on macroeconomic, microeconomic, and climate projections. In comparison with the outcomes from a business-as-usual scenario, emissions trading allows the economy to perform better in terms of GDP growth, macroeconomic stability, and employment while mitigating the temperature anomalies and fostering the clean energy transition.

The recent public debate around the possible inclusion of climate-altering emissions in the Industrial Emissions Directive (IED) of the European Union was the inspiration to build further scenarios, wherein emissions are regulated through operational permits in line with the polluter pays principle. Operational permit scenarios mimic the provisions of relevant environmental regulations such as the IED itself and the US Clean Air Act. By comparing emissions trading and operational permit systems, we contribute to the debate with a two-fold goal: for one, ranking alternative policy approaches (tradable vs. non-tradable permits); secondly, in case a clear ranking cannot be established, identifying the dimensions of permitting systems that lead to superior climate-economy performances. In this respect, our analysis shares the same spirit as Lamperti et al. (2020), who used the DSK model to compare market-based and command-and-control climate policies.

We consider operational permit scenarios wherein all firms need permits to operate (decentralised permits) or when only larger firms - and therefore larger emitters - need them (centralised permits). Permits are alternatively assumed in all sectors or in only specific sectors of the economy. Firm-level emissions limits are set according to the Best Available Techniques (BATs), corresponding in the model to the emissions by firms using machineries characterised by the highest environmental friendliness. Non-compliant firms are subject to penalties equal to a profit share until their emissions return within the regulatory limits. In further operational permit scenarios, we assume that the regulator requires the non-compliant firms to implement, within a given time horizon, corrective measures involving their R&D and machinery replacement policies.

Simulation results reveal that emissions trading systems do not dominate operational permit systems, performance-wise. Fine-tuning the institutional details of the permit systems can lead either tradable or non-tradable permits to outperform. For instance, economic and climate projections are better in a centralised operational permit system with corrective measures, than in an ETS with a fixed number of permits. As an implication, proposals to move climate-altering emissions under the IED regulation are not unreasonable. The second message we receive from our simulations, though, is that the best operational permit system (centralised with corrective measures) underperforms with respect to the ETS with a declining number of permits, which is superior in terms of GDP growth, employment, firm survival, firm size, temperature anomalies mitigation, and the likelihood of a green transition, although the performance gap is far from astounding. A third and equally relevant implication of our study is that corrective measures centred on R&D and technology adoption over a relatively short time horizon are effectively promoting climate-economy performance, despite the fact that R&D outcomes are uncertain and lengthy to achieve.

Our proposed explanation for the comparative performances of ETS and operational permits relies on the set of financial flows induced by the permit systems. Operational permit systems do not provide "positive" incentives to mitigate emissions. Unlike in the operational permit system, in an ETS firms below the emissions limit receive a payment, as they can sell the excess allowances to non-compliant firms. As a result, virtuous firms in ETS scenarios have larger revenues than comparable firms in operational permit scenarios and can use them to fund R&D projects, improve their productivity (as well as energy efficiency and environmental friendliness), win market shares, and mitigate their bankruptcy risk.

The favourable ranking for an ETS with a declining number of operation permits and, hence, higher compliance cost may be partly due to some simplifying assumptions in our modelling of emissions trading. The use of carbon offsets may dampen the mitigation of GHG attained through ETS (Haya et al., 2020). Hence, had we assumed offsets, our ETS may have been dominated by operational permits in terms of GHG mitigation. Our model is a better representation of systems that rely less on carbon offsets, such as the ETS linking Quebec and California, where only 8% of allowances can be generated through offsets. For comparison, in Phases 2 and 3 of the EU-ETS emitters could use offset to cover up to 50% of their allowances (Green, 2021). Still, our results on the transition towards green energy sources and about energy demand dynamics are in line with the common finding that ETS tend to yield their benefits mainly through fuel switching and efficiency improvements (Tvinnereim and Mehling, 2018).

Still, further ways of structuring environmental permit systems would deserve to be studied. To keep the model complexity within reasonable limits, we have not explored alternative penalty rules, e.g. proportional to violations or to the expected climate damage. To the extent that small firms are individually responsible for relatively small damages, such penalties may be less penalising for them than for larger firms, and therefore should lead to fewer firm failures and worker layoffs.

Another question is whether penalties on profits are more or less penalising for healthy firms. One may argue that inefficient firms with profits close to zero would pay lower fines, whereas an operational permit system would clip the wings of highly profitable firms. In fact, experiments not shown in the paper suggest that penalties on revenues lead to even more bankruptcies.[18]

An additional issue in permit design that would deserve exploration is multi-dimensional permits. According to the IED, operational permits require compliance with emissions limits as well as minimal energy efficiency levels. In the DSK model, firms invest in R&D to improve the energy efficiency of machines. Therefore, a possible extension of the analysis may feature penalties applied to firms that do not reach a regulatory level of energy efficiency even when their GHG emissions are below regulatory limits. This could exacerbate the market selection process, causing a faster exit of energy-inefficient firms and allowing newborn firms to tap into an improved set of technological opportunities. The outcome should be a faster rate of energy efficiency improvement in the aggregate. At the same time, though, including energy efficiency floors would have blurred the comparison with tradable emission allowances. Markets for energy efficiency (or "white") certificates would need to be modeled. Future applications of the DSK model in this area may proceed along these lines.

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[18] To see why, let R and C denote revenues and costs, respectively, and $\theta \in (0,1)$ be the penalty. Suppose the penalty is on revenues. Therefore, the post-penalty profits on a non-compliant firm are $\theta \cdot R - C$. Consider the same firm (with the same costs and revenues) if penalties are on profits. Post-penalty profits are $\theta \cdot (R - C) = \theta \cdot R - \theta \cdot C$. It is easy to verify that profit-wise, firms are disproportionally penalised by penalties on revenues, and therefore failures are higher.

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Appendix A The model

A.1 The capital good sector

Capital-good firms' technology is defined by a set of six firm-specific coefficients composed by $A^k_{i,\tau}$, with $k = L, EE, EF$, which represents the technical features of the machine produced, and $B^k_{i,\tau}$, which represents the features of the production technique employed by firm i, with τ being the technology vintage. Given the monetary wage which is paid to workers at a given time, $w(t)$, and the current cost of energy, $c^{en}(t)$, the unitary cost of production for capital-good firm i is given by

$$c_i^{cap}(t) = \frac{w(t)}{B^L_{i,\tau}} + \frac{c^{en}(t)}{B^{EE}_{i,\tau}}. \tag{12}$$

Firms define their price by applying a fixed mark-up ($\mu_1 > 0$) on their unit cost of production defined by the nominal wage, nominal cost of energy, labour productivity, and energy efficiency. Capital-good firms can increase both their process and product technology levels via (costly) innovation and imitation. Indeed, R&D expenditures, defined in each period as a fraction of past sales are split between both activities according to the parameter $\xi \in [0, 1]$.

The innovation process has two steps: first a random draw from a Bernoulli distribution with parameter $\theta_i^{in}(t) = 1 - exp^{\varsigma_1 INNOV_i(t)}$ determines whether firm i innovates or not, with $0 \leq \varsigma_1 \leq 1$. Note that higher amounts of R&D expenditures allocated to innovation, $INNOV_i(t)$, increase the probability to innovate. If an innovation occurs, the firm draws the technical parameters of the new technology from a Beta distribution (see Lamperti et al., 2018, for details). The imitation process is similarly performed in two steps. A Bernoulli draw ($\vartheta_i^{im}(t) = 1 - exp^{\varsigma_2 IMIT_i(t)}$) defines access to imitation given the imitation expenditures, $IMIT_i(t)$, with $0 \leq \varsigma_2 \leq 1$. In the second stage, a competitor technology is imitated, based on an imitation probability which decreases in the technological distance (computed adopting Euclidean metrics) between every pair of firms. Note that the innovative and imitation processes are not always successful as the newly discovered technology might not outperform firm i's current vintage. The comparison between the new and incumbent generations of machines is made taking into account both price and efficiency. Next, capital-good firms advertise their machine's price and productivity by sending a "brochure" to potential customers (both to historical clients, $HC_i(t)$, and to a random sample of potential new customers, $NC_i(t)$ consumption-good firms thus have access to imperfect information about the available machines.

A.2 The consumption good sector

Consumption-good firms produce a homogeneous good using two types of inputs (labor and capital) with constant returns to scale. The desired level of production Q^d_j depends upon adaptive expectations $D^e_j = f[D_j(t-1), D_j(t-2), ..., D_j(t-h)]$, desired inventories ($N^d_j$), and the actual stock of inventories (N_j): $Q_j(t)^d = D^e_j(t) + N^d_j(t) - N_j(t)$, where $N_j(t) = \iota D^e_j(t)$, $\iota \in [0, 1]$.

Similarly to capital good sector, the unitary production cost of a firm j in the consumption-good industry buying machines of vintage τ from capital-good firm i is

$$c_j^{con}(t) = \frac{w(t)}{A^L_{i,\tau}} + \frac{c^{en}(t)}{A^{EE}_{i,\tau}}. \tag{13}$$

Consumption-good firms' production is limited by their capital stock ($K_j(t)$). Given the desired level of production firms evaluate their desired capital stock (K^d), which, in case it is higher than their current one, calls for desired expansionary investment (EI^d): $EI^d_j(t) = K^d_j(t) -_j (t)$.

Each firms' stock of capital is made of a set of different vintages of machines with heterogeneous productivity. As time passes by, machines are scrapped if more productive alternatives are available. Total replacement investment is then computed at firm level as the number of scrapped machines, and those with age above η periods, $\eta > 0$. Firms compute the average productivity of their capital stock, the unit cost of production, and set prices by applying a variable mark-up on unit costs of production. Consumers have imperfect information regarding the final product (see Rotemberg, 2008, for a survey on consumers' imperfect price knowledge) that prevents them from instantaneously switching to the most competitive producer. Still, a firm's competitiveness ($E_j(t)$) is directly determined by its price, but also by the amount of past unfilled demand $l_j(t)$: $E_j(t) = -\omega_1 p_j(t) - \omega_2 I_j(t)$, where $\omega_{1,2} \geq 0$. At the aggregate level, the average competitiveness of the consumption-good sector is computed averaging the competitiveness of each consumption-good firm weighted by its past market share, f_j. Market shares are finally linked to their competitiveness through a "quasi" replicator dynamics:

$$f_j(t) = f_{j,t-1}\left(1 + \chi \frac{E_j(t) - \bar{E}_t}{\bar{E}_t}\right), \tag{14}$$

where $\chi > 0$ and $\bar{E}_t$ is the average competitiveness of the consumption good sector.

A.3 Innovation and imitation

Following Dosi et al. (2010), both innovation and imitation are modelled as two step processes. The first one captures the stochastic nature of technical change, and determines the access to the subsequent phase through a draw from a Bernoulli distribution, where the amount invested in R&D affects the likelihood of success. The second step determines the size of the technological advance. In the case of imitation, firms accessing the second step are given the opportunity to copy characteristics of production techniques and machines of the closest competitor in the technological space.[19] The second step for innovation, instead, entails an additional stochastic component. In particular,

$$A^k_{i,\tau+1} = A^k_{i,\tau}(1 + \chi^k_{A,i}) \quad \text{for } k = L, EE \tag{15}$$

$$B^k_{i,\tau+1} = B^k_{i,\tau}(1 + \chi^k_{B,i}) \quad \text{for } k = L, EE \tag{16}$$

and

$$A^{EF}_{i,\tau+1} = A^{EF}_{i,\tau}(1 - \chi^{EF}_{A,i}) \tag{17}$$

$$B^{EF}_{i,\tau+1} = B^{EF}_{i,\tau}(1 - \chi^{EF}_{B,i}), \tag{18}$$

where $\chi^k_{A,i}$ and $\chi^k_{B,i}$ are independent draws from $Beta(\alpha^k, \beta^k)$ distributions over the supports $[\underline{x}^k, \overline{x}^k]$, respectively for $k \in \{L, EE, EF\}$. The support of each distribution defines the potential size of the technological opportunity along the corresponding dimension.

A.4 Financial sector: banking industry

Our financial system is relatively stylized. We assume a banking sector composed by a unique commercial bank (or multiple identical ones) that gathers deposits and provides credit to firms. In what follows, we first describe how credit demand is calculated by each firm. Next, we discuss how total credit is determined by the bank, and how credit is allocated to each firm.

The financial structure of firms matters (external funds are more expensive than internal ones) and firms may be credit rationed. Consumption good firms have to finance their investments as well as their production and start by using their net worth. If the latter does not fully cover total production and investment costs, firms borrow external funds from the bank. Total production and investment expenditures of firms must therefore satisfy the following constraint

$$c_j(t)Q_j(t) + EI_j(t)^d + RI_j(t)^d \leq NW_j(t)^d + Deb_j(t)^d,$$

where $c_j(t)Q_j(t)$ indicates total production costs, $EI_j(t)^d$ expansion investment, $RI_j(t)^d$ replacement investment, $NW_j(t)$ the net worth and $Deb_j(t)$ is the credit demand by the firm. Firms have limited borrowing capacity: the ratio between debt and sales cannot exceed a maximum threshold: the maximum credit demand of each firm is limited by its past sales according to a loan-to-value ratio $0 \leq \lambda \leq +\infty$. The maximum credit available in the economy is set through a credit multiplier rule. More precisely, in each period the

[19] The technological space is thought to be a 4-dimensional Euclidian space where ℓ^2 is chosen as the metric determining distance between couples of points.

bank is allowed by the Central Bank to grant credit above the funds obtained through deposits from firms in the two industries (and equal to firms' past stock of liquid assets) according to a multiplier $k > 0$: $MTC_t = k * \sum_{j=1}^{N} NW_{j,t-1}$.

Since deposits are the only form of debt for the bank, k determines also the debt to asset ratio that should be satisfied by the bank while providing credit. Such a total credit, which generates endogenous money, is allocated to each firm in the consumption-good sector on a pecking order basis, according to the ratio between net worth and sales. If the total credit available is insufficient to fulfill the demand of all the firms in the pecking order list, some firms that are lower in the pecking order are credit rationed. Conversely, the total demand for credit can also be lower than the total notional supply. In this case all credit demand of loans of the bank satisfies the following constraint: $\sum_{j=1}^{N} Deb_j(t) = Loan(t) \leq MTC_t$.

The profits of the bank are equal to interest rate receipts from redeemable loans and from interests on reserves held at the Central Bank minus interests paid on deposits. Furthermore, the bank fixes its deposit and loan rates applying respectively a mark-down and a mark-up on the Central Bank rate.

A.5 Consumption, wages, taxes and public expenditures

The consumption of workers is linked to their wage. We assume that the wage rate, $w(t)$ is determined by institutional and market factors, with indexation mechanisms upon the inflation, average productivity, and the unemployment rate:

$$w(t) = w(t-1)\left[1 + \psi_1 \frac{\Delta \bar{AB}(t)}{\bar{AB}(t-1)} + \psi_2 \frac{\Delta cpi(t)}{cpi(t-1)} + \psi_3 \frac{\Delta U(t)}{U(t-1)}\right],$$

where $\bar{AB}$ indicates the average productivity in the economy, cpi is the consumer price index and, intuitively, U stands for unemployment rate.

The public sector levies taxes on firm profits, gathers penalties for not respecting the emission limits, and pays unemployed workers a subsidy, which corresponds to a fraction of the current market wage. In fact, taxes, penalties and subsidies are the fiscal instruments that contribute to the aggregate demand management. All wages and subsidies are consumed: the aggregate consumption (C_t) is the sum of income of both employed and unemployed workers. We notice that consumption, in this model, does not directly entail the production of emissions. The model satisfies the standard national account identities: the sum of value added of capital- and consumption-goods firms (Y_t) equals their aggregate production since in our simplified economy there are no intermediate goods, and also coincides with the sum of aggregate consumption, investment ($I_t = EI_t + RI_t$) and change in inventories (ΔN): $\sum_{i=1} Q_i(t) + \sum_j Q_j(t) = Y_t + I_t + \Delta N$.

A.6 Electricity producing technologies and costs

Demand for electricity is matched by the monopolist by producing $Q_e(t)$ from a portfolio of power plants. The plants are heterogeneous in terms of cost structures, thermal efficiencies, and environmental impacts. Green plants convert freely available, renewable sources of energy (such as wind, sunlight, water, biomass) into electrical power at a null unit production cost, i.e. $c_{ge}(t) = 0$ (ge: "green electricity"), and produce no greenhouse gas emissions. We shall assume for simplicity that green plants work at full capacity, hence the quantity of electricity that can be produced through the green technology, $Q_{ge}(t)$, is equal to its capacity $K_{ge}(t)$. Dirty plants burn fossil fuels (e.g. natural gas, coal, oil) through a process characterized by thermal efficiency A_{de}^{τ}, where the subscript de stands for "dirty electricity" and the superscript τ denotes the technology vintage. Hence, the average production cost for a dirty plant of vintage τ is given by

$$c_{de}(\tau, t) = \frac{p_f}{A_{de}^{\tau}}, \tag{19}$$

where $p_f(t)$ is the price of fossil fuels, exogenously determined on a international market.[20] Notice that electricity production is a highly capital-intensive process, which mainly requires power generation assets and resources (be them fossil fuels or renewable sources), while the labour input is minimal. We can thus assume away labour from electricity production.

The total production costs depend on which plants are used. If the monopolist wishes to economize on costs, it will be better off running all of its green plants and switching on the dirty plants only if the green capacity is insufficient to satisfy demand. Even then, the cheapest dirty plants will be used first.[21]

Let IM be the set of infra-marginal power plants, i.e. such that their total production equals demand. If $D_e(t) \leq K_{ge}(t)$, IM only includes green plants and the total production cost is zero. If $D_e(t) > K_{ge}(t)$, the total production cost measures the cost of producing electricity from the cheapest dirty power plants. Assuming that all dirty power plants have a unit capacity and consume a unit of fuel, and that the absolute frequency of vintage τ plants is $g_{de}(\tau, t)$, if dirty plants are operated the total production cost is

$$PC_e(t) = \sum_{\tau \in IM} g_{de}(\tau, t) c_{de}(\tau, t) A^{\tau}_{de}. \tag{20}$$

The dirty technology leaves a carbon footprint, in that burning fossil fuels yields em^{τ}_{de} emissions per energy unit.

A.7 Expansion and replacement investments

The capacity stock $K_e(t)$ is defined as the sum of the capacities of all power plants across technologies (green, dirty) and vintages. The capacities of individual plants are normalized to one; $g_{de}(\tau, t)$ denotes the absolute frequency of vintage-τ dirty plants (already defined above), and $g_{ge}(\tau, t)$ is the same for green plants. Then the capacity stock is equal to

$$K_e(t) = \sum_{\tau} g_{de}(\tau, t) + \sum_{\tau} g_{ge}(\tau, t). \tag{21}$$

Given that green plants produce at full capacity and dirty plants are characterized by thermal efficiencies A^{τ}_{de}, the maximum production level that can be obtained with the available capacity stock is

$$\overline{Q}_e(t) = \sum_{\tau} g_{de}(\tau, t) A^{\tau}_{de} + \sum_{\tau} g_{ge}(\tau, t). \tag{22}$$

An expansion investment is undertaken whenever the maximum electricity production level $\overline{Q}_e(t)$ falls short of the electricity demand $D_e(t)$. The amount of new expansion investments EI^d_e thus equals

$$EI_e(t) = K^d_e(t) - K_e(t), \tag{23}$$

if $\overline{Q}_e(t) < D_e(t)$, whereas $EI_e(t) = 0$ if $\overline{Q}_e(t) \geq D_e(t)$.

The expansion investment is made up of new green capacity is added whenever the following payback rule is satisfied:

$$\underline{IC}_{ge} \leq b \underline{c}_{de}, \tag{24}$$

where b is a discount factor, $\underline{IC}_{ge} = \min_{\tau} IC^{\tau}_{ge}$, and $\underline{c}_{de} = \min_{\tau} c^{\tau}_{de}$. That is, the fixed cost of building the cheapest vintage of green plants must be below the discounted production cost of the cheapest dirty plant. If so, the producer builds $EI_e(t)$ units of new green capacity and the expansion investment cost amounts to

[20] The markets for fossil fuels are globally integrated and the prices of different fuels are linked, as shown by the evidence of co-integration of their time series. There are institutional reasons for this, such as prices indexed on baskets of energy goods. For this reason, and also to keep the paper focused, we can consider fossil fuels as homogeneous in their impacts on electricity production costs.

[21] Such a merit order rule is based on the actual functioning of the electricity industry. Even before liberalization, the traditional goal of energy systems management was the minimization of system-wide electricity production, transmission, and distribution costs.

$$EC_e(t) = \underline{IC}_{ge} EI_e(t). \tag{25}$$

If instead the payback rule is not met, the entire expansion investment consists of (the cheapest) dirty plants and is undertaken at no cost ($EC_e(t) = 0$).

A.8 R&D expenditures and outcomes

The R&D expense by the electricity monopolist is a fraction $v_e \in (0, 1)$ of previous period sales.

The R&D budget is entirely employed for innovation purposes, as there are no competitors to imitate. Innovative efforts aim at obtaining new green technologies and/or new dirty technologies. Let the $S_e(t)$ be the total revenues of the energy monopolist at time t. Obviously, such revenues comprehend a portion obtained from the sale of energy produced with green technologies and, secondly, a quota from fossil-fuel ones. Now let us assume that R&D spending in each technological trajectory is proportional to the revenues obtained from the sale of energy generated therein: $RD_{ge}(t) = \xi S_{ge}(t-1)$ and $RD_{de}(t) = \xi S_{de}(t-1)$.

Immediately, one obtains that the share of R&D investment in green (or dirty) technologies is equal to the quota of previous period energy sales from that technology. This reflect the idea that market size plays a role in shaping the direction of technical change and that investments tend to cumulate on the prevailing areas.

The innovative search in the two paths is successful with probabilities $\theta_{ge}(t)$ and $\theta_{de}(t)$, conditioned on the R&D investment: $\theta_{ge}(t) = 1 - e^{-\eta_{ge} IN_{ge}(t)}$ and $\theta_{de}(t) = 1 - e^{-\eta_{de} IN_{de}(t)}$, with $\eta_{ge} \in (0, 1)$, $\eta_{de} \in (0, 1)$.

Innovation in the green technology, if successful, leads to lower fixed costs, thus encouraging the installation of green plants. Formally, the installation cost of a new vintage of green plants, IC^{τ}_{ge}, is lowered by a factor $x_{ge} \in (0, 1)$ (a random draw from a Beta distribution) with respect to the previous vintage, i.e. $IC^{\tau}_{ge} = IC^{\tau-1}_{ge} x_{ge}$.

A successful innovation in the dirty technology, instead, works through a better thermal efficiency and the abatement of greenhouse gas emissions; the efficiency and emissions of a new dirty technology (vintage τ) are represented as a pair $(A^{\tau}_{de}, em^{\tau}_{de})$, related to the existing values as follows:

$$A^{\tau}_{de} = A^{\tau-1}_{de}(1 + x^{A}_{de}) \qquad em^{\tau}_{de} = em^{\tau-1}_{de}(1 - x^{em}_{de}), \tag{26}$$

where x^{A}_{de} and x^{em}_{de} are independent random draws from a Beta distribution.[22]

A.9 Climate module and carbon cycle

As in Goudriaan and Ketner (1984) and Oeschger et al. (1975), our carbon cycle is modeled as a one-dimensional compartment box. Atmospheric CO_2 evolve according to anthropogenic emissions and oceans and biomass intakes.

Terrestrial net primary production (NPP), grows with CO_2 stocks (Wullschleger et al., 1995) and is negatively affected by rising temperatures:

$$NPP(t) = NPP(0)\left(1 + \beta_C log\frac{C_a(t)}{C_a(0)}\right)(1 - \beta_{T_1} T_m(t-1)),$$

where $C_a(t)$ represent the stock of carbon in the atmosphere, T_m is the increase in mean surface temperature from the pre-industrial level (corresponding to $t = 0$), β_C is the strength of the CO_2 fertilization feedback (Allen Jr, 1990; Allen Jr and Amthor, 1995; Matthews, 2007), and T_1 captures the magnitude of the temperature effect on NPP. In line with the recent findings of Zhao and Running (2010), we model a negative effect of global warming on NPP as in Sterman et al. (2012). This constitutes the first positive climate-carbon feedback in our model.

[22] A more realistic depiction of green energy technologies would set their thermal efficiencies far below 100% (i.e. they can only convert a relatively small fraction of the energy they receive from renewable sources) and allow for efficiency-improving innovations. Higher thermal efficiency allows a faster amortization of the fixed construction cost. The way we model innovation in green technologies, however, yields the same effects, because a lower fixed construction cost allows to anticipate the break-even point, too.

The concentration of carbon in the atmosphere depends also on the structure of exchanges with the oceans. The latter are represented by a two-layer eddy diffusion box which simplifies Oeschger et al. (1975). The equilibrium concentration of carbon in the mixed layer, C_m, depends on the atmospheric concentration and the buffering effect in the oceans created by carbonate chemistry:

$$C_m(t) = C_m^*(t) \left[\frac{C_a(t)}{C_a(0)} \right]^{\frac{1}{\xi(t)}},$$

where C_m^* is the reference carbon concentration in the mixed layer, $C_a(t)$ and $C_a(0)$ are the concentrations of atmospheric carbon at time t and at the initial point of the simulation, and $\xi(t)$ is the buffer (or Revelle) factor. The Revelle factor rises with atmospheric CO_2 (Goudriaan and Ketner, 1984;Rotmans, 1990) implying that the oceans' marginal capacity to uptake carbon falls as its concentration in the atmosphere increases. Moreover, rising temperature also reduces seawater solubility of CO_2 (Fung, 1993; Sarmiento et al., 1998), introducing another climate-carbon cycle positive feedback which accelerate climate change by reducing C_m^* (Cox et al., 2000). Finally, CO_2 is gradually transferred from the mixed to the deep layer of the oceans according to a speed that varies with the relative concentration of carbon in the two layers.

The flux of carbon though atmosphere, biosphere and oceans affects the heat transfer across the system and, hence, the dynamics of Earth surface mean temperature. Such a relationship is modelled through Eqs. 6 and 7 in the main text, and mediated by the accumulation of carbon, and leads to global warming through increasing radiative forcing according to a logarithmic relationship:

$$F_{CO_2}(t) = \gamma log \left(\frac{C_a(t)}{C_a(0)} \right).$$

Equation above represents the main link between anthropogenic emissions, which contribute to increase the concentration of carbon in the atmosphere at any period, and climate change, which is induced by the radiative forcing of atmospheric GHGs. On the other side, global warming exerts two important feedbacks on the dynamics of carbon, affecting its exchanges with the biosphere and the oceans.

Appendix B Parameters of the model

Description	Symbol	Value
General parameters		
Monte Carlo replications	MC	100
Time sample in economic and climate system	T	400/600
Number of firms in capital-good industry	F_1	50
Number of firms in consumption-good industry	F_2	200
Capital-good firms' mark-up	μ_1	0.04
Consumption-good firm initial mark-up	$\bar{\mu}_o$	0.28
Energy monopolist mark-up	μ_e	0.01
Uniform distribution supports	$[\varphi_1, \varphi_2]$	$[0.10, 0.90]$
Wage setting $\Delta \bar{AB}$ weight	ϕ_1	1
Wage setting Δcpi weight	ϕ_2	0
Wage setting ΔU weight	ϕ_3	0
R&D investment propensity (industrial)	ν	0.02
R&D allocation to innovative search	ξ	0.5
Firm search capabilities parameters	$\zeta_{1,2}$	0.3
Share of energy sales spent in R&D	ν_e	0.01
Beta distribution support (innovation)	$[\chi_1, \bar{\chi}_1]$	[-0.1,0.1]
New customer sample parameter	ϖ	0.5
Desired inventories	l	0.1
Physical scrapping age (industrial)	η	20
Physical scrapping age (energy)	η_e	80
Payback period (industrial)	b	3
Payback period (energy)	b_e	10
Penalty rate (industrial)	f	0.041
R&D allocation for corrective measure	ζ	0.2
Cutoff factor on payback period	δ	1
Emissions cut factor	Ω	0.0105
Scaling parameter for permit price	ι	0.02
Emission limit (capital)	$\bar{Em}^c$	3.2
Emission limit (consumption)	$\bar{Em}^c$	2.6
Emission limit (energy)	$\bar{Em}^e$	4.1
Climate box main parameters and initial conditions		
Initial (2000) share of green energy		0.1
Preindustrial Global Mean Surface Temp.	T_{pre}	$14C^{\circ}$
Preindustrial carbon in the ocean (per meter)		10.237 GtonC
Preindustrial reference CO2 in atmosphere	Ca_0	590 GtonC
Preindustrial Net Primary Production	NPP_{pre}	85.177 GtonC/year
Initial carbon in the atmosphere		830.000 GtonC
Initial carbon in deep oceans		10,010.000 GtonC
Initial temperature in atmosphere	T_0	14.800 C°
Response of primary production to carbon conc.	β_C	1 Dmnl
Reference buffer factor	revelle	9.7 Dmnl
Index for response of buffer factor to carbon conc.	deltaC	3.92 Dmnl
Eddy diffusion coefficient for circulation in oceans	d_{eddy}	1 Dmnl
Mixed oceans depth	d_{mixed}	100 m
Deep oceans depth	d_{deep}	3500 m
Sensitivity of carbon uptake to temperature by land	β_{TC}	-0.01 $1/C^{\circ}$
Sensitivity of carbon uptake to temperature	β_T	0.003 $1/C^{\circ}$
Diffusion for atmospheric temperature equation	c_1	0.098
Equilibrium climate sensitivity	λ	2.9 C°
Diffusion in deep oceans temp. equation	c_3	0.088
Radiative forcing coefficient	γ	5.35 W/m2
GtC to GtCO2 conversion factor		3.67

Table 9: Main parameters and initial conditions in the economic system and climate box.
Note: For previous parametrisation of some sub-portions of the model and for model sensitivity to key parameters see Dosi et al. (2010, 2013); Lamperti et al. (2018).