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And Then He Wasn't a She: Climate Change and Green Transitions in an Agent-Based Integrated Assessment Model

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And Then He Wasn't a She: Climate Change and Green Transitions in an Agent-Based Integrated Assessment Model

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Abstract

In this work, we employ an agent-based integrated assessment model to study the likelihood of transition to green, sustainable growth in presence of climate damages. The model comprises heterogeneous fossil-fuel and renewable plants, capital- and consumption-good firms and a climate box linking greenhouse gasses emission to temperature dynamics and microeconomic climate shocks affecting labour productivity and energy demand of firms. Simulation results show that the economy possesses two statistical equilibria: a carbon-intensive lock-in and a sustainable growth path characterized by better macroeconomic performances. Once climate damages are accounted for, the likelihood of a green transition depends on the damage function employed. In particular, aggregate and quadratic damage functions overlook the impact of climate change on the transition to sustainability; to the contrary, more realistic micro-level damages are found to deeply influence the chances of a transition. Finally, we run a series of policy experiments on carbon (fossil fuel) taxes and green subsidies. We find that the effectiveness of such market-based instruments depends on the different channels climate change affects the economy through, and complementary policies might be required to avoid carbon-intensive lock-ins.

Keywords: climate change; agent based models; transitions; energy policy; growth.
JEL: C63, Q40, Q50, Q54.

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1 Introduction

How does climate change impact on the transition from fossil-fuel to low carbon technologies? According to our results, quite a lot. While the literature analysing transitions is large and variegate, there is a gap on how climate change can affect the likelihood and speed of decoupling economic growth from fossil fuels and the ensuing macroeconomics effects. In the present work, we fill this gap relying on an agent-based integrated assessment model where energy transitions are endogenous and co-evolve with climate change and can be possibly affected by policy interventions.

Economic growth must be sustained by energy production. Different portfolio of energy sources can support the same rate of growth at different costs, which change over time according to the technological evolution. However, once the possible impacts of climate change are taken into account, economic growth ought to be *sustainable*, i.e. it must be decoupled from greenhouse gas (GHG) emissions. Indeed, as pointed out by the literature on high-end scenarios, the environmental, health, and physical damages triggered by climate change may outpace any adaptation effort, hampering long-term growth prospects and ultimately treating the very existence of life as we know it. Thus, long-term economic growth cannot be a credible objective without treating the green transition as an unavoidable goal of public policy-making. And as climate change, technical change and economic growth co-evolve over time, increasing research efforts are required to understand if the speed of transition implicitly defined by the international climate agreements is fast enough, and whether policies are effective.

Against this background, traditional integrated assessment models (IAMs) are badly equipped to study the role of firm and energy plant heterogeneity and the sources and direction of technical change triggering successful energy transition towards sustainability. Further, climate damages are often measured in percentages of GDP losses, under the implicit assumption that, due to linearity in the economic system, the aggregate shock is plainly the sum of microeconomic shocks. While being empirically questionable, such a perspective does not allow policy-makers to identify from where in the economic system the risks and costs of climate change originate and propagate, thus affecting the transition to sustainable growth. More generally, the microeconomic analysis of energy transitions has little to say about the ensuing macroeconomic dynamics (Stirling, 2014; Mazzucato and Semieniuk, 2017).

The Dystopian Schumpeter meeting Keynes (DSK; Lamperti et al., 2018b) agent-based model constitutes a viable platform to analyze the energy transition while dealing with all the above mentioned issues.[1] In particular, DSK accounts for endogenous technical change in the three sectors it comprises, namely capital goods, consumption goods, and energy. Technical change is the outcome of boundedly rational R&D decisions by heterogeneous agents, who finance R&D through retained earnings and (rationed) credit, and whose effect is stochastic. Firms also engage in technological diffusion as they adopt or imitate new vintages of machinery, characterized by heterogenous levels of labor productivity, energy efficiency, and environmental friendliness.

In the energy sector, firms can choose between fossil-fuel and renewable plants. Brown energy plants have higher production costs than green one, but have zero installation costs, while firms has to pay a fixed cost to expand their renewable energy capacity. Energy firms invest in R&D

[1] Agent based models are flexible computational environments simulating the behaviour of complex systems, nowadays widespread in different areas of the social sciences (Bonabeau, 2002; Tesfatsion and Judd, 2006; Haldane and Turrell, 2018). The interested reader might want to look at Fagiolo and Roventini (2012) and Fagiolo and Roventini (2017) for two surveys on macro agent based models and to Balint et al. (2017) and Lamperti et al. (2018a) for agent based applications to the issue of climate and environmental change.

a fraction of its past sales in order to develop the green and dirty technologies. Industrial and energy productions generate GHG emissions, whose effect on climate is modelled in a climate box. Once temperatures change, the economy is hit by microeconomic climate shocks affecting, labor productivity or energy efficiency of machines, and in turn macroeconomic dynamics.

The DSK model is able to account for a wide range of micro and macro stylized facts concerning economic dynamics and the evolution of climate change (e.g. self-sustained growth punctuated by endogenous crises, co-integration of energy and output dynamics, increasing frequency of extreme events). Simulation results show that, even without considering climate damages, the model produces a non-ergodic behaviour characterized by two statistical equilibria: a carbon-intensive lock-in, wherein the share of renewable energy plants approaches zero; and an equilibrium wherein the transition to green energy technologies is successful. In the latter case, GDP growth is faster,and unemployment lower than in the carbon-intensive lock-in, suggesting that sustainable growth can improve macroeconomic dynamics.

Once climate damages are accounted for, the likelihood of green transition depends on the damage function employed. When climate shocks are modelled as aggregate output losses, as commonly done in the majority of general-equilibrium IAMs (Nordhaus and Sztorc, 2013; Nordhaus, 2014), climate shocks do not affect the probability of carbon decoupling. However, when one focuses on the different channels through which microeconomic climate damages hit firms, the results are more complex. More specifically, negative shocks to energy efficiency are found to slow down the transition, whereas shocks reducing labor productivity accelerate it. Both effects interact with the dynamics of energy demand and prices, which affect the investment of energy firm in green and dirty technologies. Finally, the success of policies supporting sustainable growth such as carbon tax and green subsidies depends on the different channels through which climate damages affect the economy, and complementary command-and-control interventions are often required to avoid carbon-intensive lock-ins

The paper is structured as follows. After a brief review of the relevant literature in Section 2, we describe the model in Section 3. The model is empirically validated in Section 4. Simulation results focused on transition to sustainable growth are presented in Section 5. Finally, Section 6 concludes.

2 A critical review of the literature

The literature on transitions to sustainable production modes is large and variegate (Frantzeskaki and Loorbach, 2010; Markard et al., 2012). From a theoretical perspective, four main frameworks have been developed to analyse the issue. These include transition management (Rotmans et al., 2001; Loorbach, 2010), strategic niche management (Kemp et al., 1998), the multi-level perspective on socio-technical transitions (Geels, 2002), and technological innovation systems (Jacobsson and Johnson, 2000; Jacobsson and Bergek, 2011). Embracing different perspectives they have been used to analyse shifts in socio-technical systems. In this context, a *socio-technical system* consists of (networks of) actors (individuals, firms, and other organizations, collective actors) and institutions (societal and technical norms, regulations, standards of good practice), as well as material artifacts and knowledge (Geels, 2004; Weber, 2003). A sustainable transition involves moving from a given socio-technical system to a novel one characterized by production and consumption modes reducing the adverse impact on the natural system. Socio-technical transitions differ from technological transitions in that they include changes in user practices and institutional (e.g., regulatory and cultural) structures, in addition to the technological dimension. In this paper, we loosely focus on the technological dimension but, contrary to the approaches introduced above, we look at the aggregate (i.e. macroeconomic) effect of moving away from fossil-fuels technologies.

In that, we contribute to a recent stream of studies focusing on economies' growth dynamics and the composition of the energy mix. The mainstream economic literature has employed models of directed technical change to explore how policy can move economic development and R&D activities away from fossil fuels (Acemoglu et al., 2012, 2015). As a central result, they report that both subsidies to "green" research and carbon taxes should be used to move the economy towards a sustainable growth trajectory. Despite they call for a marginal and temporary intervention, Lamperti et al. (2015) show that such market based policies might be ineffective as a result of path-dependence and put forward regulation as a valid alternative policy to induce transitions.[2] Moving the attention from R&D to resource availability, other contributions have analysed the optimal trajectory from non-renewable to renewable resources and highlighted the role of renewables' production costs in inducing the transition (Hoel and Kverndokk, 1996; Ploeg and Withagen, 2014; Van Der Ploeg and Withagen, 2012).[3] This feature will be crucial also in our model. Interestingly, while the majority of studies underlines the importance of shifting to renewable energy sources, Smulders and Zemel (2011) highlight possible drawback effects on economic growth linked to crowding-out effects in capacity building. However, they do not account for climate change/environmental damages. Another main shortcoming of such a research body is that it fails to account for the complex relationships tying agents in an economic system, and too heavily relies on the capacity of markets in efficiently allocating both resources and knowledge. In such a context, inducing a transition loosely boils down at finding the correct set of incentives.

Starting from different theoretical constructs and a more realistic representation of the economy, the literature on macro agent based and system dynamics modelling has recently moved towards the analysis of energy transitions, macroeconomic dynamics and policy choices (Balint et al., 2017; Lamperti et al., 2018a). Such a stream builds on the perception of the economy as a complex evolving system (Arthur et al., 1997; Tesfatsion, 2006; Dosi and Virgillito, 2017) and, departing from this basis, looks at the evolutionary mechanisms behind technological development, technological diffusion, and technological transitions with a particular emphasis on energy and environmental issues (Van Den Bergh and Gowdy, 2000; Safarzyńska et al., 2012).[4] This is particularly relevant as sustainability challenges are robustly coupled with and aggravated by the strong path-dependencies, and ensuing lock-ins, we observe in the existing sectors (Åhman and Nilsson, 2008; Unruh, 2000; Safarzyńska and van den Bergh, 2010). Under such conditions, endogenous sustainable transitions can be viewed as positive tipping points, whose determinants needs investigation (Tbara et al., 2018). Both demand and supply sides matter in shaping the final technological landscape. Bleda and Valente (2009) investigate the role of demand induced innovations and eco-labelling in fostering the transition to greener production modes. Safarzynska and van den Bergh (2011) study the role of boundedly-rational investors in driving technological development within the energy indus-

[2] See also Smulders et al. (2011) on the role of regulation in triggering transitions, and Eriksson (2018) for the social desirability of a long run perpetual public support of green technologies.

[3] The interested reader might want to look at Gillingham et al. (2008) for a survey on technical change modelling in mainstream environment-climate-economy models.

[4] We refer the interested reader to Nelson and Winter (1982) and Dosi (1988) for the evolutionary background on technological change, to Tesfatsion and Judd (2006), Farmer and Foley (2009) and Bonabeau (2002) for background material, and to Fagiolo and Roventini (2012) and Fagiolo and Roventini (2017) for excellent surveys on recent developments in macro agent based modelling.

try, highlighting that the emergent energy mix might strongly depend on the investing heuristics. Gualdi and Mandel (2016) and Ponta et al. (2018) focus instead on technological diffusion, and study the effects of stylized feed-in tariffs. The first contribution finds that feed-in tariffs are relatively more effective than preferential market access in supporting the diffusion of radical (green) innovation, with positive consequences on the dynamics of growth. The second study, instead, reports a trade-off: for moderate policy strength the economy benefits from the transition, while for high policy intensity investments crowd-out consumption and increase interest rates. Our paper contributes to the debate, as it study the effects of public subsidies to green energy technologies and, symmetrically, taxes on fossil-fuel ones.

However, the key ingredient we add to the picture is the representation of climate damages. Transitions involve a broad range of actors and typically unfold over considerable time-spans (e.g., 50 years and more, Markard et al., 2012). This is further confirmed by the length of the simulations conducted in the battery of studies reported above and, more specifically, by that the length of the transition itself. Over such long horizons, it is crucial to consider how climate change could affect the economic system and, therefore, the dynamics of the transition. Both in the mainstream economic and complex system literatures, climate damages are either overlooked or vaguely represented as utility losses (Greiner et al., 2014), thereby failing to consider the wide array of impact channels identified by the nascent literature on climate econometrics (Hsiang, 2016; Carleton and Hsiang, 2016). In this respect, we take advantage of the DSK model (Lamperti et al., 2018b), where different micro-level shocks can be modelled and, therefore, we also link to the Integrated Assessment literature Weyant (2017) which, usually, takes into consideration endogenous technical change but oversee the macroeconomic impacts of transitions.

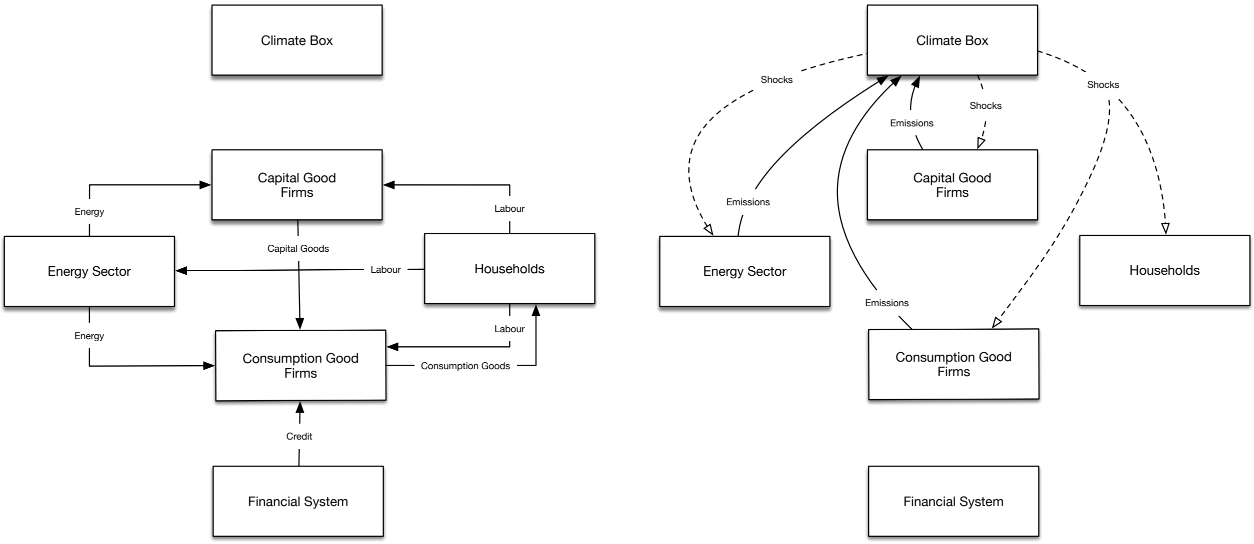
3 The model

The DSK model (Lamperti et al., 2018b) represents a complex economy endowed with a climate box. Economic and climatic variables co-evolve interacting non-linearly, with multiple feedbacks, and emerging tipping points. A graphical representation of the model is provided in Figure 1.

The economic dynamics is grounded on Dosi et al. (2010, 2013) and is composed by two industrial sectors, whose firms are fueled by an energy industry. In the capital-good sector, firms invest in R&D and innovate to improve the performances of the machines in terms of productivity, energy-efficiency and environmental friendliness. In the manufacturing industry, firms invest in machine-tools in order to produce an homogeneous product consumed by workers and they can rely on credit to finance their production and investment plans.[5]

Energy and industrial production emit greenhouse gasses (e.g. CO2), which in turn affect the evolution of the temperature. More precisely, we model a stylized global carbon cycle which drives the projections of Earth's radiative forcing and, finally, the global mean surface temperature. The impact of an increase in the temperature of the Earth on economic dynamics is modeled through a stochastic, time-evolving, disaster generating function (as in Lamperti et al., 2018b). In particular, the probability of large climate shocks hitting firms raises in tandem with the mean size of damages. In that, climate change does not automatically lead to higher aggregate damages as in most IAMs, but rather it modifies the very structure of the economy and the ensuing economic growth (or lack

[5]See Dosi et al. (2016) for a survey of the K+S model family, to which DSK belongs, and Dosi et al. (2017c) for a recent development.



(a) economic flows (b) climate flows

Figure 1: A graphical representation of the DSK model; source Lamperti et al. (2018b).

of). As a benchmark, we also use a standard damage function cutting aggregate output in a linear way as in Nordhaus and Sztorc (2013). The details of the DSK model are spelled out in Appendix A.

3.1 Industrial sectors

The economy features a capital-good industry and a consumption-good sectors. Firms in the capital-good industry produce machines employing labour and energy. Different vintages of machines are characterized by different *productivity of labour*, *energy efficiency* and *environmental friendliness*. The unit cost of production of both capital- and consumption-good firms depends on labor productivity, workers' wage (w), energy efficiency, as well as energy price (p^e). Machines and production technologies induce CO2 emissions via both their electricity consumption (indirect effect) and their environmental friendliness, i.e. the amount of polluting substances they emit in each period for each unit of energy employed throughout the production process.

Technical change and innovation occur in the capital-good sector. Firms invest in R&D a fraction of their past sales in order to discover new machines or copy the ones of their competitors. New machines can be more productive, cheaper, or "greener". Innovation and imitation are modeled as two step stochastic processes. In the first step, the amount invested in R&D affects the likelihood of success. In the second one, technological opportunities determines the size of innovation. In the case of imitation, firms are more likely to copy the competitions with the closest technologies.

The capital-good market is characterized by imperfect information and competition. Capital-good firms strive to get new customers 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. Machine-tool firms fix price a constant mark-up on the unit cost of production. Time-to-build constraints characterized the production of machines: consumption-good firms receive their new capital-goods at the end of the period.

Consumer good-firms produce a homogeneous good using their stock of machines, energy and labour under constant returns to scale. Firms plan their production according to adaptive demand expectations. If the current capital is not sufficient to satisfy the desired level of production, they buy new machines. As machine embed state-of-the-art technologies, innovations diffuse from the capital- to the consumption good sector. Relatedly, technical change can also induce firms to replace their current stock of machines with more productive (and environmental friendly) ones. Firms' gross investment is simply the sum of expansion and replacement investments.

Consumption-good firms finance their investments as well as their production relying on imperfect capital markets (Stiglitz and Weiss, 1981; Greenwald and Stiglitz, 1993). Firms first rely on their stock of liquid assets and then on bank credit. The borrowing capacity of firms is limited by their ratio between debt and sales. The bank provides loans to consumption-good firms on a pecking order basis, considering their net worth-to-sales ratio. If credit supply is lower then demand, some firms end up being credit rationed.

Consumption-good firms first produce and they try to sell their product in the market. Hence, production do not necessarily coincide. Consumption-good market is characterized by imperfect competition: firms fix price according to a variable mark-up which evolve reflecting the dynamics of market shares. In presence of imperfect information, demand is allocated through a quasi replicator dynamics, wherein firms competitiveness depends on their price and they successfully satisfied their past demand. Details and equations are collected in Appendix A.

3.2 The energy sector

3.2.1 Electricity production, costs and and revenues

Energy production is performed by a set of heterogeneous power plants featuring green (renewable) or brown (carbon-intensive) technologies. The energy industry produces and sells electricity to firms in the capital-good and consumption-good industries on demand. Demand for electricity, D_e, is then matched by the aggregate energy production, Q_e, obtained from the portfolio of plant. Energy cannot be stored.

Plants are different in terms of their technical coefficients reflecting cost structures, thermal efficiencies and environmental impacts. Brown plants burn fossil fuels (e.g. coal, oil) with heterogeneous, vintage-specific thermal efficiency A^{τ}_{de}, which expresses the amount of energy produced for each unit of employed non-renewable resource (fossil-fuel).[6] For simplicity, we assume that power plants have a unitary capacity and, in the case of brown energy, they consume one unit of fuel. Hence, the average production cost for a brown plant of vintage τ is:

$$c_{de}(\tau, t) = \frac{p_f}{A^{\tau}_{de}}, \tag{1}$$

where p_f is the price of fossil fuels, exogenously determined on a international market.[7] Burning fossil fuels yields em^{τ}_{de} emissions per energy unit, thus increasing the carbon concentration in the atmosphere.

To the contrary, the carbon footprint of green plants is zero. They transform freely available, renewable sources of energy (such as wind and sunlight) into energy units at a null production

[6] The subscript *de* stands for "dirty electricity", while τ denotes the technology vintage.

[7] 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 thus assume away labour from electricity production.

cost, i.e. $c_{ge}(t) = 0$ (ge, "green energy").[8]

The total production costs depends on the mix of green and dirty plants. We assume that plants with the lowest unitary generation costs are the first to be activated, in line with the actual functioning of the electricity industry (Sensfuß et al., 2008; Clò et al., 2015). Indeed, even before liberalization, the traditional goal of energy systems management was the minimization of system-wide electricity production, transmission, and distribution costs. In turn, this imply that green plants are the first to be turned on. More precisely, if $D_e(t) \leq K_{ge}(t)$, the set of infra-marginal power plants IM includes only green plants and the total production cost is zero. If $D_e(t) > K_{ge}(t)$, the total production cost corresponds to the cheapest dirty power plants. Assuming the absolute frequency of vintage τ plants is $g_{de}(\tau, t)$, if dirty plants are operative the total production cost is:

$$PC_e(t) = \sum_{\tau \in IM} g_{de}(\tau, t) c_{de}(\tau, t) A^{\tau}_{de}. \tag{2}$$

The energy price is computed adding a fixed markup $\mu_e \geq 0$ to the average cost of the more expensive infra-marginal plant:

$$p_e(t) = \mu_e, \tag{3}$$

if $D_e(t) \leq K_{ge}(t)$, and

$$p_e(t) = \bar{c}_{de}(\tau, t) + \mu_e \tag{4}$$

if $D_e(t) > K_{ge}(t)$, where $\bar{c}_{de}(\tau, t) = \max_{\tau \in IM} c_{de}(\tau, t)$. By setting a markup on this unit cost level, there is a positive net revenue on all infra-marginal plants.[9]

3.2.2 Expansion and replacement investments

In order to fulfil energy demand, new power plants might be necessary. Moreover, old and obsolete plants should be replaced as well. In particular, we assume that all (brown and green) plants have a constant life-time corresponding to η_e periods. All new plants are built in house (i.e. within the energy sector), but their production cost is technology specific. Specifically, the construction costs for new dirty plants are normalized to zero, whereas in order to install a new green plant of vintage τ, a fixed cost IC^{τ}_{ge} needs to be sustained.

The capacity stock $K_e(t)$ is obtained summing up the capacities of all power plants across technologies (green vs. dirty) and vintages. Recalling that the capacity of plants is normalized to one and denoting with $g_{de}(\tau, t)$ and $g_{ge}(\tau, t)$ the absolute frequency of dirty and green plant respectively, one gets:

$$K_e(t) = \sum_{\tau} g_{de}(\tau, t) + \sum_{\tau} g_{ge}(\tau, t). \tag{5}$$

For a given capacity stock, the maximum production level that can be obtained depends on the thermal efficiencies A^{τ}_{de} of dirty plants (green plants produce at full capacity):

$$\overline{Q}_e(t) = \sum_{\tau} g_{de}(\tau, t) A^{\tau}_{de} + \sum_{\tau} g_{ge}(\tau, t). \tag{6}$$

[8] Some renewable sources, such as wind and photovoltaics, are intermittent and non-dispatchable: their output is highly volatile at high temporal frequencies as it depends on weather conditions that cannot be controlled by the power plant operator. However, our model runs on temporal frequencies that are relevant for macroeconomics, such as annual or quarterly. Over those time horizons, the average output from intermittent renewable is fairly predictable.

[9] In the aggregate perspective of our model, market power exercise through markups can be seen as equivalent in its effects to alternative strategies, such as capacity withholding.

An expansion investment in the energy industry is undertaken whenever the maximum electricity production level $\overline{Q}_e(t)$ is lower than electricity demand $D_e(t)$. The amount of new expansion investments EI_e^d thus equals

$$EI_e(t) = K_e^d(t) - K_e(t), \tag{7}$$

if $\overline{Q}_e(t) < D_e(t)$, whereas $EI_e(t) = 0$ if $\overline{Q}_e(t) \geq D_e(t)$. A choice is available between green or brown new plants. We assume that new green capacity is constructed if green plants are cheaper than brown counterparts in terms of accounting lifetime costs. This means that green energy technologies are chosen up whenever fixed cost of building the cheapest green vintage is below the discounted (variable) production cost of the most efficient dirty plant. Hence, the following payback rule is satisfied:

$$\underline{IC}_{ge} \leq b \cdot \underline{c}_{de}, \tag{8}$$

where b is a payback period parameter (e.g. Dosi et al., 2010, 2013), $\underline{IC}_{ge} = \min_\tau IC_{ge}^\tau$, and $\underline{c}_{de} = \min_\tau c_{de}^\tau$. Accordingly, in case of new green capacity, the expansion investment cost amounts to

$$EC_e(t) = \underline{IC}_{ge} EI_e(t); \tag{9}$$

whereas it is zero if the payback rule is not met and the firm builds new dirty plants.

3.2.3 Technological innovation

The technology of green and dirty plants change over time as result of innovations. The energy firm invests a fraction $v_e \in (0, 1)$ of total past sales in R&D. Total revenues $S_e(t)$ are generated from both green and brown energy sales, i.e. $S_e(t) = S_{ge}(t) + S_{de}(t)$. R&D investment in each technological trajectory is proportional to the revenues obtained from the sale of energy generated therein:

$$RD_{ge}(t) = v_e S_{ge}(t-1) \tag{10}$$

and

$$RD_{de}(t) = v_e S_{de}(t-1). \tag{11}$$

Such an assumption is coherent with the evolutionary literature on selection processes and technical change (Nelson and Winter, 1982; Dosi et al., 2010) and, further, reflects 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 (Acemoglu, 2002; Acemoglu et al., 2012).

We model innovation as a two stage stochastic process as in the capital- and consumption good sectors. More precisely, the innovative search in the two paths is successful with probabilities $\theta_{ge}(t)$ and $\theta_{de}(t)$, conditioned on the R&D investment:

$$\theta_{ge}(t) = 1 - e^{-\eta_{ge} IN_{ge}(t)} \tag{12}$$

$$\theta_{de}(t) = 1 - e^{-\eta_{de} IN_{de}(t)} \tag{13}$$

with $\eta_{ge} \in (0, 1)$, $\eta_{de} \in (0, 1)$. Successful innovators can then access to the second stage where they project a new green or dirty plant. Innovation along the green technological trajectory reduce the installation fixed costs. Formally, the installation cost of a new vintage of green plants, IC_{ge}^τ, is lowered by a factor $x_{ge} \in (0, 1)$ (a random draw from a Beta distribution) with respect to the previous vintage:

$$IC_{ge}^{\tau} = IC_{ge}^{\tau-1} x_{ge}. \tag{14}$$

Innovation in dirty technology can improve plants' thermal efficiency and reduce greenhouse gas emissions. The thermal efficiency and emissions intensity coefficients $(A_{de}^{\tau}, em_{de}^{\tau})$ of the new vintage τ of dirty technology are given by:

$$A_{de}^{\tau} = A_{de}^{\tau-1}(1 + x_{de}^{A}) \qquad em_{de}^{\tau} = em_{de}^{\tau-1}(1 - x_{de}^{em}) \tag{15}$$

where x_{de}^{A} and x_{de}^{em} are independent random draws from a Beta distribution.[10]

3.2.4 Profits and liquid assets

Energy sold to the capital- and consumption-good industry is paid in advance. Hence, the total profits realized in the energy industry reads:

$$\Pi_e(t) = S_e(t) - PC_e(t) - IC_e(t) - RD_e(t) \tag{16}$$

where $S_e(t)$ indicate energy sales, $PC_e(t)$ are production costs, $IC_e(t)$ denotes expansion and replacement investment, and $RD_e(t)$ are R&D expenditures. At the end of the period, the stock of liquid assets in the energy sector is accordingly updated:

$$NW_e(t) = NW_e(t-1) + \Pi_e(t). \tag{17}$$

3.3 Climate change and climate damages

A climate model is added to our economic system to fully endogenize the relationship between climate change and the growth pattern of the economy. In particular, we rely on a discrete-time version of the C-ROADS model described in Sterman et al. (2012, 2013). Such model accounts in a parsimonious away for the complex physical and chemical relations governing climate's evolution, especially including the multiple feedbacks responsible for non-linear dynamics. Note that while the economy reacts quarterly, the climate module updates annually.

A core carbon cycle, whose details are included in Appendix A, takes the annual emissions from the industry and the energy sector as input and models carbon exchanges between the atmosphere, the biomass and the oceans. The latter two elements constitute the main in-take channels, whose dynamics are affected by the temperature through two main feedback loops. Then, the equilibrium concentration of carbon in the atmosphere impacts the size of the Earth's radiative forcing and finally, the evolution of the temperature.

In particular, building on Schneider and Thompson (1981) and Nordhaus (1992), the heat content of the two layers (upper layer: atmosphere and surface of oceans; lower layer: deep oceans) is modulated by their reciprocal exchanges and, with respect to the upper compartment, by the CO_2

[10] 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.

radiative forcing (F_{CO_2}):[11]

$$T_m(t) = T_m(t-1) + c_1 \{F_{CO_2}(t) - \lambda T_m(t-1) - c_3[T_m(t-1) - T_d(t-1)]\} \quad (18)$$

$$T_d(t) = T_d(t-1) + c_4 \{\sigma_{md}[T_m(t-1) - T_d(t-1)]\}, \quad (19)$$

where T_i is the temperature in the different layers relative to pre-industrial levels, R_i is the thermal inertia in the two boxes, λ is a climate feedback parameter, F_{CO_2} represents the radiative forcing in the atmosphere from greenhouse gasses (relative to pre-industrial levels), and σ_{md} is the transfer rate of water from the upper to lower ocean layers 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.

How does climate change affect economic dynamics? In most IAMs, the negative impact of rising temperatures on the economy is simply captured via an aggregate damage function expressing fractional losses of GDP.[12] Apart from the difficult (and often arbitrary) choice of parameters, one issue with the use of such aggregate damage function is that it does not distinguish among different microeconomic impact channels. Is climate change reducing labour productivity? Is it increasing capital depreciation? Or, is it augmenting, caeteris paribus, energy demand? And are firms and households hit in the same way?[13]

A recent econometric strand of literature is increasingly focusing on the analysis of climate damages, thus providing empirical estimates to answer such questions. Carleton and Hsiang (2016) propose a survey of recently investigated climate impacts on labour productivity, labour supply, mortality, electricity consumption and a series of other variables. There is little doubt that such micro impacts will manifest, in aggregate terms, through a variation of final income. However, disentangling the various channels, the possible heterogenous impacts on agents, and their effects on the behaviour of the economy remains under-investigated.

The DSK model relys on stochastic *agent-based damage generating function*, which endogenously evolve according to the dynamics of the climate. Such a function simply takes the form of a density and, at the end of each period, multiple draws establish the size of the shocks hitting firms and workers. Notably, shocks are heterogeneous across agents and across economic variables, with only a subset of firms facing climate disasters. Given its flexibility, we take advantage of a Beta distribution over the support $[0, 1]$, whose density satisfies:

$$f(s; a, b) = \frac{1}{B(a, b)} s^{a-1}(1-s)^{b-1}, \quad (20)$$

where $B(\cdot)$ is the Beta function and a, b are respectively the location and scale parameters. Both

[11]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. It is then an index of the importance of the factor as a potential climate change mechanism (IPCC, 2007b). To simplify we use CO_2 as a proxy for all green house gases and we consider only its radiative forcing.

[12]For example, Nordhaus (2008) uses an inverse quadratic loss function, Weitzman (2009) proposes a negative exponential specification emphasizing the catastrophic role of large climate changes, while Tol (2002) uses sector and area specific loss function.

[13]For more extensive and circumstanced critiques to the existing damage functions see Ackerman et al. (2010) and Pindyck (2013).

Table 1: Summary statistics on selected variables under business-as-usual scenario and no climate shocks, and comparison with historical empirical counterparts.

	MC average	MC st. dev.	Empirical counterpart	Data source
Yearly GDP growth	0.032	0.004	0.044	WDI
Unemployment rate	0.088	0.021	0.061	WDI
Energy demand growth	0.028	0.003	0.023	WDI
Emissions growth	0.013	0.001	0.018	CDIAC
Relative volatility of consumption	0.64	0.03	0.79	FRED
Relative volatility of investments	1.95	0.05	2.77	FRED
Volatility of output	0.258	0.013	0.0157	FRED
Likelihood of crises	0.10	0.065	-	-
Share of green energy at 2100	0.50	0.22	-	-
Emissions at 2100	26.81	9.510	-	-
Temperature at 2100	4.45	0.543	-	-

Note: All values refer to a Monte Carlo of size 200. 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 preindustrial level, which is assumed to be 14 Celsius degrees. WDI stands for World Development Indicators, provided by the World Bank. Empirical counterparts are computed over large time spans, but are subject to data availability: World real GDP, unemployment and CO_2 emissions data refer to the period from 1980 to 2010; employed energy consumption data go from 1991 to 2013; quarterly data for volatility analysis are from 1970 to 2002 and refer to the US economy, but the reported features are quite robust across countries, see also Stock and Watson (1999); Napoletano et al. (2006). Volatilities are expressed as standard deviations of bandpass filtered series; relative volatilities use output volatility as comparison term. A crisis is defined as an event where the yearly loss of output is higher than a 5% threshold. Growth rates computed as $(y_{\text{final}} - y_{\text{initial}})/(y_{\text{initial}} * T)$.

parameters are assumed to evolve across time reflecting changes in climate variables:

$$a(t) = a_0[\log(1 + T_m(t))] \tag{21}$$

$$b(t) = b_0 \frac{\sigma_{10y}(0)}{\sigma_{10y}(t)}, \tag{22}$$

where $\sigma_{10y}(t)$ is a measure of the variability of surface temperatures across the previous decade and a_0, b_0 are positive integers.[14] Equations (21) and (22) shape the disaster generating function as a right-skewed, unimodal distribution, whose mass moves along the positive axis as temperature increases, thereby raising the likelihood of larger shocks. Equation (22) determines the size of the right tail of the distribution and allows to account for the importance of climate variability on natural disasters (Katz and Brown, 1992; Renton et al., 2014).

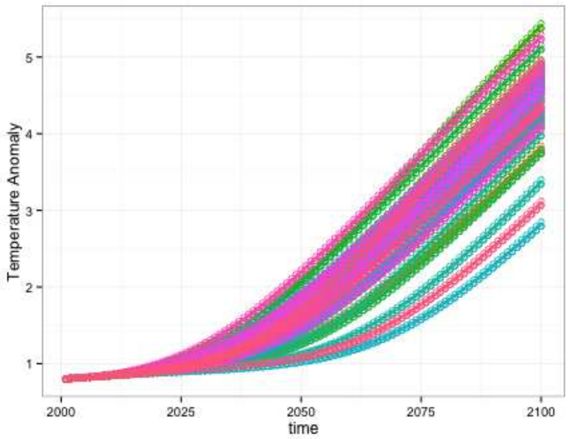
Formally, climate shocks hit the economy at the end of each period according to the following specification:

$$X_{i,\tau}(t) = X_i'(t)[1 - \hat{s}_i^x(t)], \tag{23}$$

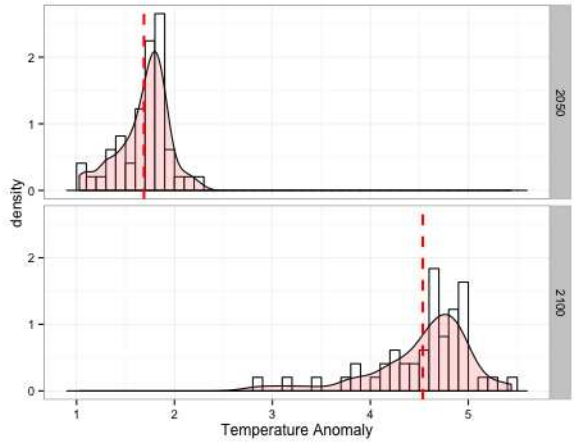
where i indexes firms in the economy, $\hat{s}^x(t)$ is the draw from the disaster generating function, while $X(t)$ captures the target impact variable one wants to study. In the simulation experiments below, we will focus on labor productivity and energy efficiency characterizing machines and production techniques.

[14] For modelling purposes we estimate the standard deviation of previous ten recorded temperatures; however, a widely used measure of climate variability corresponds to the count of extreme temperatures.

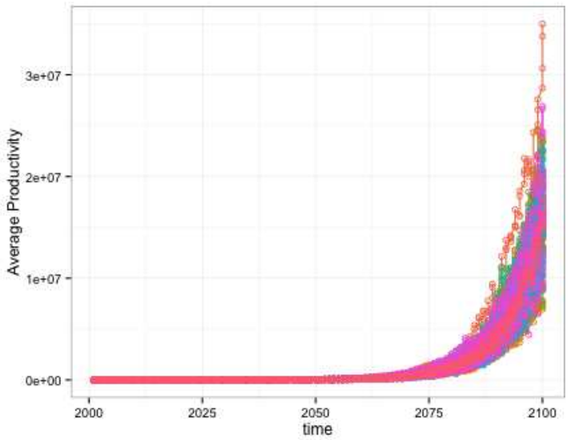
Figure 2: Temperature projections and their density estimates.



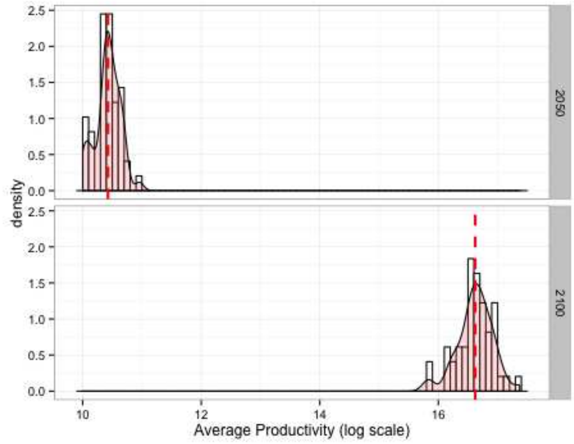
(a) Temperature projections.



(b) Distribution of temperature.



(c) Average firm productivity projections.



(d) Distribution of average firm productivity.

Note: All panels show 50 model runs under different seeds of the pseudo-random number generator. Red dashed lines in panel 2b indicate mean values. In panel 2d the x-axis is in logarithmic scale.

4 Empirical validation

We start exploring whether the DSK model can account for micro and macro empirical regularities concerning economic and climate dynamics. The DSK model should be considered as a global model. In its baseline (benchmark) configuration, the model runs in absence of climate damages and the parametrization reported in Appendix B.

In line with the indirect calibration approach discussed in Windrum et al. (2007) and Fagiolo et al. (2007) and following the prevailing practice in the agent based macro modelling literature (see the survey in Fagiolo and Roventini, 2012, 2017), the parameters of the DSK models have been selected to reproduce six empirical features of the real world system.[15] More precisely, simulated data should account for: (i) presence of self-sustained growth and business cycles punctuated by

[15]In a nutshell, the indirect calibration approach first identifies a set of empirical features that the model wants to match, then employs a search strategy to select points into the parameter space and finally test weather the identified empirical properties are robustly present in the simulated series. For a survey of validation approaches in the macro ABM literature we refer the interested reader to Fagiolo et al. (2017) and to the literature review sections in Lamperti (2017a,b) and Guerini and Moneta (2017).

Table 2: Main empirical stylized facts replicated by the DSK model. Source: Lamperti et al. (2018b).

Stylized facts	Empirical studies (among others)
Macroeconomic stylized facts	
SF1 Endogenous self-sustained growth	Burns and Mitchell (1946); Kuznets and Murphy (1966)
with persistent fluctuations	Zarnowitz (1985); Stock and Watson (1999)
SF2 Fat-tailed GDP growth-rate distribution	Fagiolo et al. (2008); Castaldi and Dosi (2009)
	Lamperti and Mattei (2016)
SF3 Recession duration exponentially distributed	Ausloos et al. (2004); Wright (2005)
SF4 Relative volatility of GDP, consumption, investments and debt	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	Wälde and Woitek (2004)
SF7 Cross-correlations of credit-related variables	Lown and Morgan (2006); Leary (2009)
SF8 Cross-correlation between firm debt and loan losses	Foos et al. (2010); Mendoza and Terrones (2012)
SF9 Pro-cyclical energy demand	Moosa (2000)
SF10 Syncronization of emissions dynamics and business cycles	Peters et al. (2012); Doda (2014)
SF11 Co-integration of output, energy demand and emissions	Triacca (2001); Ozturk (2010); Attanasio et al. (2012)
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 heterogeneity across firms	DeCanio and Watkins (1998); Petrick et al. (2013)

endogenous crises; (ii) average growth rate of output between 2.5% and 3.5%; (iii) average unemployment rate between 5% and 15% percent; (iv) investment more volatile than output, consumption less volatile than GDP; (v) growth rate of energy consumption lower than growth rate of output, but higher than the growth rate of emissions, (vi) growth rate of emissions lower than the growth rate of output, but consistent with RCP 8.5, (vii) projected temperature anomaly at 2100 in line with the ranges relative to RCP 8.5.[16]

The simulation protocol adopted to inspect the baseline configuration employs 400 simulation steps, which should be interpreted as quarters. Accordingly, the model can simulate and project GDP and temperature dynamics till the year 2100 as commonly done by integrated-assessment models. To wash away the effects due to stochastic terms, we performs Monte Carlo exercises of size 200 on the seed of pseudo random number generator. The same protocol will be maintained throughout the paper.

Simulation results show that the baseline DSK model is consistent with the seven requested conditions introduced earlier and, further, it reasonably matches the long run empirical counterparts of many key variables (e.g. growth paces of output and energy demand; see Table 1). The economy exhibits endogenous fluctuations and self-sustained growth (3.2% on average; see also Figure 2) punctuated by crises, emissions grow at an average pace that is close to those observed in the last 30 years and energy intensity to GDP is decreasing over time as suggested by the empirical evidence. In addition, final projections of total emissions (average of 26.81 GtC at 2100) are in line with those produced in the business-as-usual scenario by many other integrated assessment models used by the IPCC (Clarke et al., 2009; Nordhaus, 2014). Moreover, the projections of temperature anomaly over pre-industrial levels are consistent with RCP 8.5 and show an average of 4.45 Celsius degrees (see Figure 2).

Beyond these general features, the DSK model jointly reproduces a large ensemble of micro and macro stylized facts characterizing short- and long-run behavior of modern economies. Table

[16] RCP stands for Representative Concentration Pathways; they describe four possible climate futures, all of which are considered possible depending on how much greenhouse gases are emitted in the years to come. RCP 8.5 is the most pessimistic scenario and reflects a world without policy intervention, uncontrolled emissions and high energy demand. See Riahi et al. (2011) for details.

Table 3: Percentages of non-rejection of statistical equilibrium and ergodicity tests.

	baseline		carbon lock-in		transition to green	
Variable	Equilibrium	Ergodicity	Equilibrium	Ergodicity	Equilibrium	Ergodicity
Output	0.85	0.83	0.95	0.91	0.90	0.89
Average productivity	0.91	0.89	0.96	0.92	0.89	0.86
Emissions	0.46	0.41	0.95	0.91	0.89	0.88
Temperature	0.74	0.72	0.92	0.90	0.85	0.83

Note: The results come from $T(T-1)/2$ and $T \cdot M$ pairwise comparisons for equilibrium and ergodicity respectively.

2 reports the main empirical regularities replicated by the model together with the corresponding econometric evidence. Relevantly, from a long run perspective, the model matches co-integration relationships between output, energy demand and emissions. Moreover, growth rates and duration of recessions display fat-tailed distributions, pointing to the fact that crises are more frequent that what expected in a Gaussian world. As a consequence, macroeconomic volatilities are relevant and should be also taken into account in climate change economic analysis as advocated by e.g., Rogoff (2016). Indeed, from a short run perspective, we find that DSK exhibits business cycles properties akin to those observed in developed economies: investments are lumpy and more volatile than output and consumption, R&D expenditures are pro-cyclical and tend to anticipate the economy's fundamentals. This, in particular, supports the idea that technical change is a relevant element in directing the pattern of growth. Finally, we notice that emissions and GDP are strongly synchronized, which suggest a careful interpretation of emission slow-downs.[17]

5 Green transitions and climate change dynamics

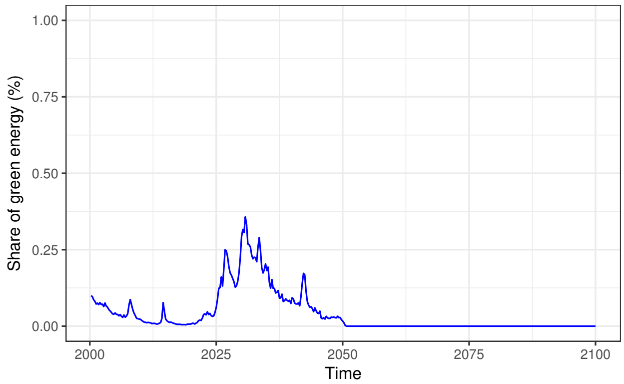
Let us now consider under which conditions a green transition to a sustainable growth path can emerge and if such a process is characterized by path-dependency and possible carbon lock-ins. More specifically, we adopt the following strategy. First, we study green transitions switching off climate-change shocks (cf. Section 5.1). In this way, by isolating the economy from the possible negative impacts of climate change, we can focus on the economic processes and constrains affecting the energy choices of firms. We then introduce feedbacks from climate change to economics dynamics, thus studying the co-evolution of the economy and the climate (see Section 5.2). Finally, we analyze the possible policy interventions to support the transition to a sustainable growth path grounded on renewable energies (Section 5.3).

5.1 Green transition in an economy with zero climate-change impacts

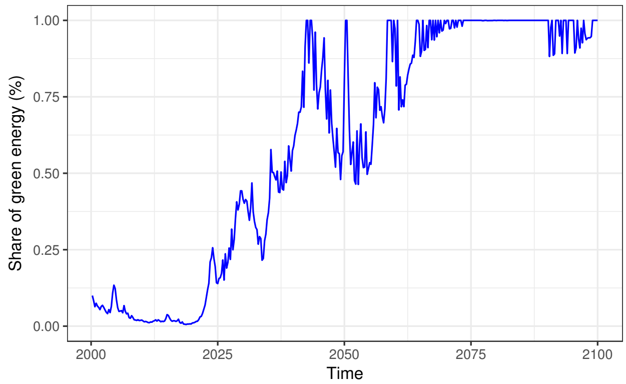
We begin considering the adoption of green vis-à-vis dirty energy technologies and we study the ensuing economic dynamics assuming that higher level of temperatures never trigger climate shocks. This is a strong assumption as a closer scrutiny of Figure 2 suggests that the model projects temperature anomaly at the end of the century well above 4 degrees in the vast majority of cases. However, in some simulation runs, temperature growth is much less pronounced and it does not

[17]For a more detailed analysis of the empirical regularities that the model reproduces, together with their formal investigation, we refer the reader to Lamperti et al. (2018b).

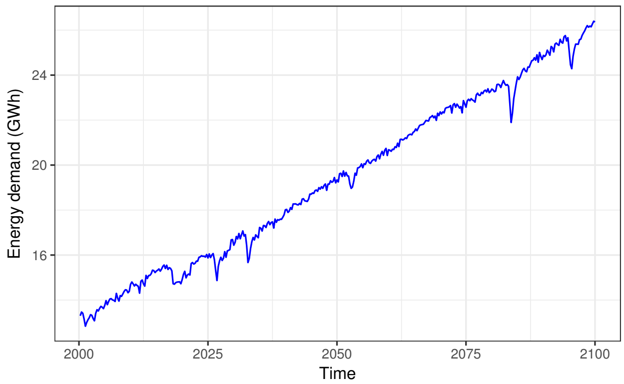
Figure 3: Example of runs where a carbon lock in or a green transion occurs.



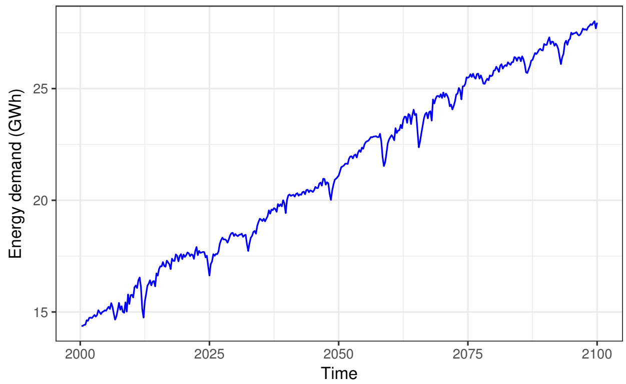
(a) Share of green energy production - Lock in.



(b) Share of green energy production - Transition.



(c) Energy demand - Lock in.



(d) Energy demand - Transition.

Table 4: Kolmogorov-Smirnov tests for difference between equilibria.

Variable	Kolmogorov-Smirnov test statistic	p-value	Test-type	N
Output growth	0.2125	0.1017	two-sided	200
Emissions growth	0.4438	0.0000	two-sided	200
Emissions at 2100	0.8250	0.0000	two-sided	200
Temperature at 2100	0.5688	0.0000	two-sided	200

Note: output and emission growth are averages over the whole time span.

exceed the 3 degrees threshold at 2100. Since the model is run in a business-as-usual (BAU) scenario, i.e. without mitigation and adaptation policies, two reasons could explain the observed patterns. First, the economy growth's engine could loose momentum, thereby reducing aggregate production, emissions and, finally, climate change. Second, the economy endogenously changes its energy mix and, in some cases, moves away from fossil-fuels to renewables, thus reducing the increase in temperature.

To disentangle the two possible effects, we rely on a series of formal tests for stationarity and ergodicity of stochastic simulation models (Grazzini, 2012; Guerini and Moneta, 2017; Dosi et al., 2017b). Such tools allow checking whether a model exhibits one or more statistical equilibria. In a nutshell, the model runs in an ergodic statistical equilibrium state if the properties of the series it generates are constant. In particular, we will first study whether the series (or a transformation of them) have distributional properties that are time-independent. Then, we will test whether the series are ergodic, meaning that the unknown stochastic process selecting the observed time series can be treated as a random sample. Following Guerini and Moneta (2017), we simulate the model in its baseline configuration, transform the data removing trends (if necessary), and collect them in a $M \times T$ matrix, where $M = 200$ represents the size of the Monte Carlo experiment and $T = 400$ the simulation length. Then, we use a series of Kolmogorov-Smirnov tests on pairs of series to detect the presence of a statistical equilibrium and its ergodicity. In particular, the model can be considered in a statistical equilibrium if a good proportion (e.g., 90%, as suggested in Guerini and Moneta, 2017) of tests do not reject the null hypothesis of equality of distributions, where each of these distributions is obtained polling data relative to the same simulation period but to different MC runs. Further, the statistical equilibrium is said to be ergodic if a good proportion (90%) of Kolmogorov-Smirnov tests confirm that distributions across time and seeds do not differ. In particular, ergodicity is determined by checking the equality of pairs of distributions, where the first is obtained pooling observations across time (within the same MC run) and the second pooling observations across runs (at the same time). Additional details on tests for statistical equilibria and their ergodicity are included in Appendix C. In what follows, we focus on 4 variables: (i) GDP, (ii) average productivity, (iii) emissions and (iv) temperature, where trends are removed through logarithmic differences.

Table 3 presents the percentage of non-rejections of the Kolmogorov-Smirnov tests carried out for each pairwise comparison of series. It clearly shows that the time series delivered by DSK model do not appear to exhibit one statistical equilibrium and ergodicity. Emissions and temperature anomaly appear to drive such a result. In particular, the very low non-rejection rate for emissions suggests that different dynamics of climate change may be closely linked to the energy mix adopted in the economy.

In turn, we find that the model produces a *non-ergodic* behaviour characterized by *two statistical equilibria*, each encompassing model runs characterized by specific dynamics of the share of green energy production (cf. Figure 3 and the last columns of Table 3). A *carbon intensive lock in* occurs whenever in a given run, the share of green energy drops below 15% and never rises again. Conversely, in the *transition to green* outcome, the share of green energy reaches the 85% threshold and never fall back afterward. As the energy market employ the cheapest power plant first (see Section 3), the transition toward sustainable growth occurs under comparable energy demand patterns observed in the carbon lock in cases. This suggests that the emergent energy mix depends on the relative competitiveness of different technologies, rather than on market design elements. A battery of Kolgomorov-Smirnov tests applied to average output and emission growth rates, and to the final observation (at 2100) of emissions and temperature anomaly confirm that the two statistical equilibria are statistically different in terms of model behaviour they produce, especially for climate-related variables (cf. Table 4).

Let us now investigate the behaviour of the model under carbon lock ins and green transitions. Table 5 reports the Monte Carlo average values of output growth, unemployment, emission growth, emissions and temperature at 2100, as well as their standard deviations. In addition, it further clusters runs on the basis of the timing they employ to reach their equilibrium state. As one could reasonably expect, carbon-intensive lock-ins are much more frequent (82%) than carbon decoupling outcomes (18%).[18] Moreover, we find that the most of (90%) of carbon lock-ins take place fast, i.e.

[18]In no Monte Carlo runs the share of renewable energy continues to fluctuate in way that does not allow categorization in one of the two types of equilibrium patterns.

Table 5: Likelihood of transition in the baseline configuration and main features of the different endogenous scenarios.

	Stat. Eq. I: Carbon intensive lock-in		Stat. Eq. II:Transition-to green	
Likelihood	82%		18%	
	before 2025 90%	after 2025 10%	before 2075 91%	after 2075 9%
Output growth	3.16% (0.001)	3.14% (0.002)	3.20% (0.001)	3.18% (0.004)
Unemployment	11.4% (0.016)	12.1% (0.020)	9.12% (0.019)	10.0% (0.012)
Emission growth	1.22% (0.001)	1.25% (0.002)	0.77% (0.001)	0.96% (0.002)
Emissions at 2100	28.64 (1.761)	30.12 (2.237)	18.22 (1.52)	23.13 (2.172)
Temperature at 2100	4.59 (0.103)	4.91 (0.178)	1.75 (0.123)	2.68 (0.153)

Note: all values refer to the average computed on the sub-sample of runs from a Monte Carlo of size 200 that are classified in each scenario. Standard errors are reported below each coefficient in parenthesis.

before 2025. A similar feature characterizes the transition to the sustainable scenario: when green technologies start to diffuse and reach some critical mass, their relative share with respect to dirty ones suddenly increases and they saturate the market, showing a typical S-shaped diffusion curve. Such results stems from the large investment outlays required to build renewable energy plants (in line with empirical evidence, see e.g. EIA, 2013). Moreover, a growing penetration of renewables causes a merit order effect whereby fossil-fuel plants are crowded out and the average electricity price falls (see various contributions from de Miera et al., 2008). In turn, unit production costs of capital- and consumption-good firms decline (see also Appendix A), leaving larger cash flows for investments in R%D and new green production capacity.

Our findings suggest that transition to green energy production ought to be *timely* in order to achieve sustainable growth with temperature projections below the +2 degree threshold at the end of the century. More specifically, simulation results show that transition should take place before 2030 to meet the +2 degree target and that temperature will likely rise above +3 degrees if the switch to green energy production occurs after 2075 (cf. Table 5). At the same time, economic growth is higher and unemployment rate is lower in carbon decoupling outcomes vis-à-vis fossil fuel lock-ins. Such results find in line with recent empirical evidence showing that investments in renewable energies creates substantially more jobs than in fossil fuels (Garrett-Peltier, 2017). Transitions toward sustainable growth trajectories could thus lead to *win-win* outcomes characterized by lower temperature and higher economic growth. However, the foregoing results do not account for the possible feedback effects from climate change to the economy. Let us study whether they are robust in presence of climate-change shocks hitting the economy.

5.2 Climate impacts and green transition

In the previous sections we have voluntarily excluded climate change shocks from the picture. This allowed to explore the properties of the model in absence of damages, while keeping consistency

Table 6: Likelihood of transition, economic performances and emissions under the different climate shock scenarios. Aggregate shocks use the damage function in Nordhaus and Sztorc (2013) and target aggregate output. Labour productivity and energy efficiency shocks hit individual firms.

Shock scenario:	Transition likelihood	Output growth	Energy growth	Emissions at 2100
Aggregate output	18%	3.18%	3.09%	28.33
	(of which 83% before 2025)	(0.001)	(0.003)	(6.431)
Labour productivity	20%*	1.51%*	1.16%*	25.70*
	(of which 69% before 2025)	(0.002)	(0.003)	(4.921)
Energy efficiency	7%*	3.02%	3.37%*	40.64*
	(of which 43% before 2025)	(0.003)	(0.003)	(3.872)

Note: all values refer to the average computed from a Monte Carlo of size 200. Standard errors are reported below each coefficient in parenthesis. * indicates a statistically significant (0.05 level) difference with respect to the *Aggregate output* scenario; tests for transition likelihoods are carried out via bootstrapping.

with the macro agent based and system dynamics literature on transitions (e.g. Safarzynska and van den Bergh, 2011; Ponta et al., 2016; see section 2 for details). However, as moving away from fossil fuels and developing low carbon energy capacity can take time (in our simulation the average time is around 40 years, consistent with the discussion in Markard et al., 2012), climate change is likely to exert significant effects on the transition (IPCC, 2014; Schleussner et al., 2016; Springmann et al., 2017), especially in absence of corrective policies. Here we present results from a series of computational exercises that investigate the impact of micro-level climate damages (see section 3.3) on the likelihood and feature of transitions to low carbon energy sources.

We model climate damages across three scenarios:

- *Aggregate shocks on GDP* as in traditional IAMs (Nordhaus and Sztorc, 2013; Nordhaus, 2014).
- *Micro labour productivity (LP) shocks.* Labor productivity ($A^L_{i,\tau}$ and $B^L_{i,\tau}$, see Appendix A) falls by a factor that varies across firms, as climate change negatively impacts on workers' operational and cognitive tasks (see Seppanen et al., 2003, 2006; Somanathan et al., 2014; Adhvaryu et al., 2014.
- *Micro energy efficiency (EF) shocks.* Firm-level energy efficiency ($A^{EE}_{i,\tau}$ and $B^{EE}_{i,\tau}$, see Appendix A) is reduced as climate shocks increase energy requirements in production activities (e.g. more stringent needs of cooling in response to higher temperatures and of heating in response to weather extremes, or partially ruined machines in response to natural disasters; see Auffhammer and Aroonruengsawat, 2011; Auffhammer and Mansur, 2014; Jaglom et al., 2014).

. While in the *aggregate shocks* case we adopt the damage function proposed in Nordhaus and Sztorc (2013), in the two remaining scenarios we employ the bottom-up approach described in section 3.3. In that, heterogeneous climate shocks hitting firms are drawn from a Beta distribution whose first and second moments closely follows the quadratic behaviour assumed in DICE and in a large part of the literature. Indeed, we account both for damages triggered by increases in temperature levels and variability. To provide an insight, equations 21 and 22 imply that the average individual climate shock would size about 1.46% for a temperature anomaly of 2 degrees, which becomes 3.69% at 3 degrees and 6.7% at 4. Table 6 collects the results of our comparison across the three impact scenarios.

Simulation results show that the likelihood of transitions towards green growth depends on how climate damages are modelled. In the standard aggregate perspective commonly adopted by the majority of IAMs (Table 6, upper row), the likelihood of transition is *invariant* to climate damages as shocks affect only aggregate potential output. However, when one assumes that the occurrence and magnitude of micro climate damages affects agents heterogeneously, the probability of achieving a sustainable, low emission growth pattern depends on the dynamics of climate change (cf. Table 6, middle and lower row). More specifically, shocks to labour productivity might increase the likelihood of transitions (20% vs. 18% in the case of aggregate damages), while the opposite happens for energy-efficiency shocks (only a 7% likelihood).

Such results stem from the size of the final demand for energy and the role path dependence. Indeed, if energy efficiency is reduced by climate shocks, the energetic needs to produce a given aggregate output will increase, thereby inducing the energy industry to adapt its generation capacity. Since fossil-fuel technologies start with a lower lifetime production cost, expansionary investment will favour such a technological trajectory.[19] Dynamically, this leads to a much larger spending in R&D activities aimed at improving the efficiency of brown plants, which creates a vicious cycles impeding the shift to low carbon technologies. This phenomenon turns out to dominate the dynamics, notwithstanding the penalizing effect the merit order market mechanisms exerts on brown plants.

By a similar token, shocks to labour productivity induce an increasingly sharp contraction in industrial production, wages and final demand (notice the low growth rate of output in Table 6, see also Lamperti et al., 2018b for additional details). In presence of merit order activation protocol, the lower energy demand will induce an increase in the share of green plants' production in the energy mix, which will further stimulates green R&D and improves the competitiveness of low carbon technologies. When such technologies catch-up their initial backwardness, the transition start to take place and, further self-sustains, as the marginal cost of green plants remains below the one of the brown counterparts, making them operating at increasing under-capacity.[20] At the end of their lifetime, un-activated brown plants will be replaced by green energy generation units, thus sustaining the transition.

5.3 Climate policy and green transition

Given the presence of substantial and heterogenous climate impacts, what is the role of climate policies in triggering and sustaining the transition to renewable energy sources? The last battery of simulations exercises will reply to this question. In particular, we will focus on price-related instruments, which modify the cost of fossil fuels and, in turns, the relative cost-competitiveness of green vs. brown technologies. In that, we study the imposition of an implicit carbon tax (Martin et al., 2014).[21]

In the following experiments, we assign different values to the parameter, θ, which modifies the price of fossil fuels and, in turns, the relative lifetime and production costs of brown energy plants. In particular, the unitary production cost of a fossil-fuel plant of vintage τ can be written as

$$c_{de}(\tau, t) = \frac{p_f + \theta}{A^{\tau}_{de}}. \tag{24}$$

Then, the lifetime total cost of a brown plant, $LC_{de}(t)$, is obtained, under the assumption that

[19]See also Acemoglu et al. (2012) and Aghion et al. (2015) on this point.

[20]This findings are in line with the results in Van Der Ploeg and Withagen (2012) and Ploeg and Withagen (2014).

[21]Note that a good portion of climate policies is ultimately representable through the policy effect on energy prices, which reflect the cost-structure of energy generation (Marin et al., 2017).

the plant is employed at full capacity for its entire life, by simply multiplying $c_{de}(\tau, t)$ by b_e, which represents the accountable life of the plant. On the green side (cf. section 3), unitary production costs of renwable energy plants are virtually set to zero, while installation fixed costs are represented by IC^{τ}_{ge}, which is dynamically affected by innovations in the green technological trajectory. This implies that the lifetime total cost of a green plant, $LC_{ge}(t)$, is exactly equal to IC^{τ}_{ge}. Our policy experiments focus on the ratio LC_{de}/LC_{ge}, which expresses the cost-advantage of dirty technologies. By varying the parameter θ, we modify the relative cost-competitiveness of low carbon technologies: $\theta > 0$ mimics a tax on fossil fuels or a subsidy toward investments in green energy technologies (e.g. a sort of feed-in tariff increasing the expected profitability of a green investment), whereas $\theta < 0$ captures fossil fuel subsidies, which are diffused policy instruments (Coady et al., 2017).[22]

We adopt the following simulation protocol: starting from the baseline configuration described in section 4, where brown energy technologies have a 20% cost-advantage at the beginning of the simulation[23], and we modify θ through the whole simulation time (in line with policy exercises in macro ABMs, c.f. e.g. Dosi et al., 2015; Popoyan et al., 2017; Ponta et al., 2016). Such experiments are combined with the three climate-change impact scenario described in the previous sub-section and, namely, *aggregate shocks* to GDP, *micreconomic shocks to labour productivity* and *microeconomic shocks to energy efficiency*. Figures 4 - 6 summarize our main findings.

Simulation results show that price of fossil fuels influences the likelihood of transition in a non-linear way (panels 4a, 5a and 6a). A policy-engineered increase in the cost-competitiveness of green energy technologies can increase the likelihood of a transition, regardless of the type of climate damage we assume. However, given the initially larger installed capacity of brown vis-á-vis green plants (see Appendix B) and the cumulative nature of the technical change process, small variations of the $\frac{LC_{de}}{LC_{ge}}$ ratio have a remarkable low impact on inducing the transition. In presence of sufficiently carbon tax and/or subsidies to green energy, the likelihood of achieving growth decoupled from carbon emission improves substantially. Naturally, the transition to sustainable growth is almost impossible in presence of subsidies to fossil-fuel energy plants. These results suggest that energy policy interventions needs to be *substantial* in order to significantly affect the environmental sustainability of the economy's growth process. Moreover, policies ought to be *timely* as path-dependence in the process of technological change (David, 1985; Arthur, 1994) deeply affect the policy outcome.[24]

Further, we find that the effectiveness of policy interventions also depends on the type of climate damage. As already documented in section 5.1 with respect to the likelihood of transition, policy impact differs shifting from aggregate to individual climate damage scenarios. When shocks are aggregate, consumers suffer the damage and reduce consumption, thereby cutting output levels but leaving unaltered the production schedule for the next period. In that, aggregate shocks have no memory and policy intervention is not affected by the shock. Things change when climate directly reduce productive abilities of firms. In particular, when climate change shocks affects labour productivity, policies supporting green energy technologies are substantially more effective than in the case of shocks targeting energy efficiency. Similarly to what discussed above, the size of final demand matters. When aggregate demand is lower (see panels 4b, 5b and 6b), the economy is more

[22] Note that such policy experiments are akin to a variation of the price of fossil fuels in international markets.

[23] Such an initial setting is broadly consistent with the existing estimates and modeling assumptions for energy technologies. We refer the interested reader to the series of annual reports of the IEA (`https://www.eia.gov/outlooks/aeo/`) and to Tidball et al. (2010) for information about costs of energy plants.

[24] For further readings on the role of path dependence in shaping the technological landscape, see e.g. Liebowitz and Margolis (1995); Frenken and Nuvolari (2004); Castaldi and Dosi (2006) and, more recently, Dosi et al. (2017a).

responsive to energy policies aimed at increasing the competitiveness of green technologies. On the contrary, when climate change exerts its negative effects on plants' efficiency, the final demand of energy increases, and green plants face a comparative disadvantage in terms of R&D spending, which cuts the chances of observing a surge in green energy production. As a consequence, stronger policies are required to support the transition, whose likelihood remains, however, remarkably low (17%) even when cost-advantage of brown plants is initially reduced to 1% by the policy intervention. Climate damages increasing energy demand exacerbate the role of path-dependence in the energy industry, pointing to the need for additional complementary policy instruments (e.g. command-and-control; see Lamperti et al., 2015) to market-based incentives.[25]

6 Discussion and conclusions

Climate change can impact both the process of transition towards low-carbon energy systems and the effectiveness of related policy interventions. In the paper, we have employed the DSK agent-based integrated assessment model (Lamperti et al., 2018b) to study the shift from brown (fossi-fuel based) to green (low-carbon) energy technologies and its macroeconomic implications in presence of climate change.

We find that the model exhibits two statistical equilibria (a carbon intensive lock-in and a transition to green energy) characterized by different energy mix. Transitions from brown to a green energy system might endogenously happen, but the likelihood of such events is exceptionally small and it depends on exceptional technological breakthrough.[26] Further, we found that climate change can influence the likelihood of carbon decoupling according to the way climate damages are modelled. When an aggregate and linear damage function is considered, as in the majority of general-equilibrium IAMs, the likelihood of transition is invariant to climate shocks, which simply reduce aggregate GDP. However, in presence of microeconomic climate damages, the probability of transition depends on the channels climate damages affect agents and firms. When climate shocks hit labor productivity, economic growth is reduced, but the likelihood of transition to green energy is higher. This result supports the idea that the economic environment is more responsive to climate policy in times of crisis (Jaeger et al., 2011; Ekins et al., 2014), also in line with recent systematic evaluations of the green stimulus programs implemented in the aftermath of the 2008 financial crisis in the U.S. (Mundaca and Richter, 2015). On the other side, climate damages reducing energy efficiency exacerbates the role of path-dependence in the energy industry, thereby increasing the difficulty of the catch-up process of clean energy technology.

Of course, the climate damages emerging in the present paper are somewhat downwardly biased by the fact our impact scenarios constraint shocks to a single variable (e.g. labour productivity or energy efficiency). This is - however - a necessary condition to study how different impact channels affect the macro-economy. Table 7 provides insights on the overall damage of climate change, assuming that all impacts other than those studied in the scenarios can be represented by a variable, labelled "environmental quality", which deteriorates over time by a factor corresponding to the average shock suffered by agents in that particular period (this is consistent with the similar

[25]As reported in Figure 6, in presence of energy efficiency shocks, GDP and emissions growth remains relatively high with respect to the other two scenarios, as individual damages just decrease energy efficiency, whose aggregate, macroeconomic effects are found to be limited (see the extensive discussion on macroeconomic impacts of climate change in Lamperti et al., 2018b).

[26]See also Unruh (2002) for thoughtful discussion on escaping carbon lock-ins with and without supporting policy.

Table 7: A simplified approach to welfare evaluation of climate damages in case of labour productivity and energy efficiency shocks. All values are relative to the case of no damages (a value of 100 would indicate identity with respect to the scenario where climate damages are not considered). Welfare is proxied as a simple average of normalized GDP, employment rate and environmental quality. Environmental quality degradation represents all dimensions of climate impacts other than labour productivity and energy efficiency. Environmental quality is assumed to start at 100 and decrease by a factor equal to the average climate shock suffered by agents in that period.

	GDP	Employment rate	Environmental quality	Well being index
		Labour Productivity Shocks		
2000-25	0.90	0.96	0.98	0.95
25-50	0.76	0.88	0.94	0.86
50-75	0.47	0.71	0.90	0.69
75-2100	0.21	0.48	0.84	0.51
		Energy Efficiency Shocks		
2000-25	0.96	0.99	0.98	0.98
25-50	0.88	0.99	0.94	0.94
50-75	0.87	0.93	0.90	0.90
75-2100	0.84	0.92	0.84	0.87

Note: all values refer to the average computed from a Monte Carlo of size 200.

shape damage functions show in different sectors, see Hsiang et al., 2017). Results show that in both our scenarios climate damages are substantial. For example, using a simplistic "welfare" measure averaging GDP level, employment share and environmental quality (all conveniently normalized), climate change would reduce well-being by 49% in the labour productivity shock scenario and 13% in the energy efficiency shock scenario, pointing to the need of an early green transition whatever the impact channel might actually be.

Our findings have both theoretical and policy implications. From a modelling perspective, the traditional way of representing damages in the climate economics literature in terms of GDP losses oversimplifies the effects of climate change in a complex economic system, hiding the role of climate impacts in fostering a carbon lock-in or in favoring a transition to sustainable energy. As a consequence, policies supporting the transition to sustainable growth fueled by green energy should careful consider the possible different channels through which climate damages affect the economy. Indeed, we find that the effectiveness of policies measures depends on the impact channel of climate change and that, in general terms, policies constructed around monetary incentive often produce limited results in fostering a transition whose likelihood reduces over time due to path dependence in technological change. Such results point to the necessity of rapidly taking into consideration complementary policy instruments to market-based incentives and carbon taxes of a deemed optimal size (see also Unruh, 2002; Aznar-Mrquez and Ruiz-Tamarit, 2016): regulation and adequate monitoring are often much more effective than other tools (Lamperti et al., 2015; Shapiro and Walker, 2015). Finally, one of the future developments of our model envisions the inclusion of financial actors shaping the investment-incentive landscape for different energy technologies, and points to the analysis of credit policies in addition to fiscal and regulatory initiatives as a necessary step forward in the study of green transitions.[27]

[27]The interested reader might want to look at Linnenluecke et al. (2016) for a research agenda on environmental finance.

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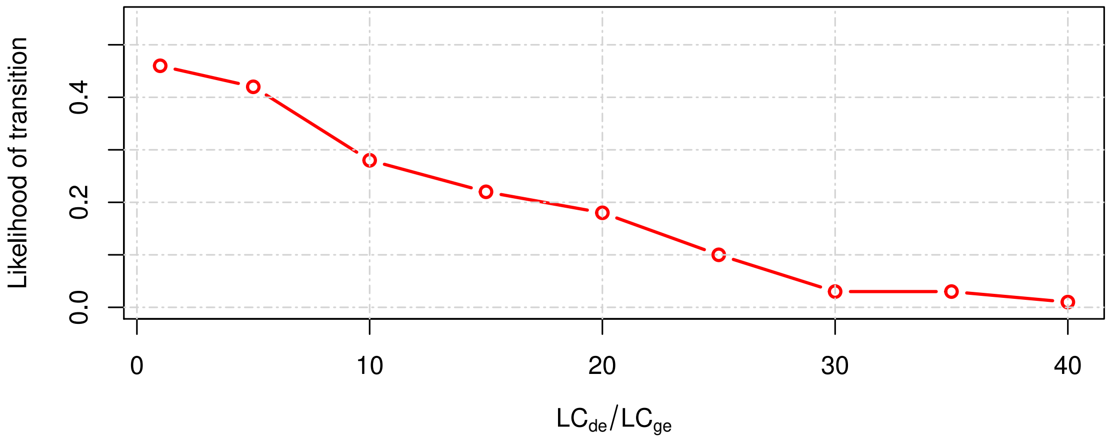
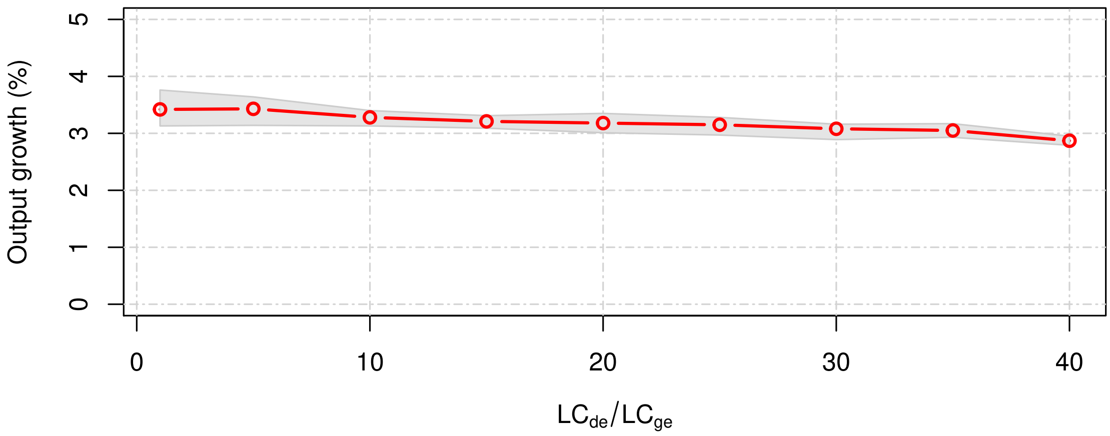
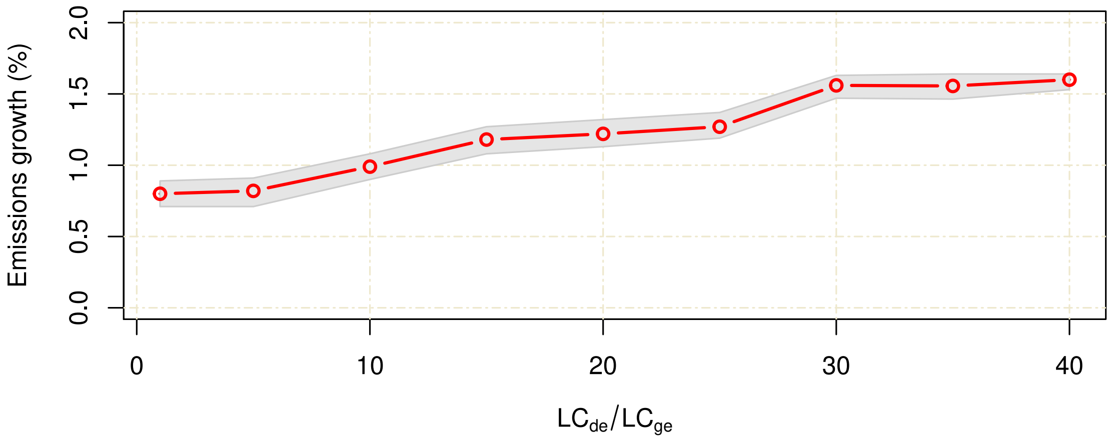
Figure 4: Likelihood of transition, average output and emissions growth under different policy strengths and aggregate climate damages as in (Nordhaus and Sztorc, 2013). LC_{de}/LC_{ge} represents the relative cost-advantage of brown energy technologies at the beginning of the simulation; 20% is the baseline. MC of size 200 is used, shaded area represents 90% percentile interval.



(a) Likelihood of transition - Aggregate shocks.

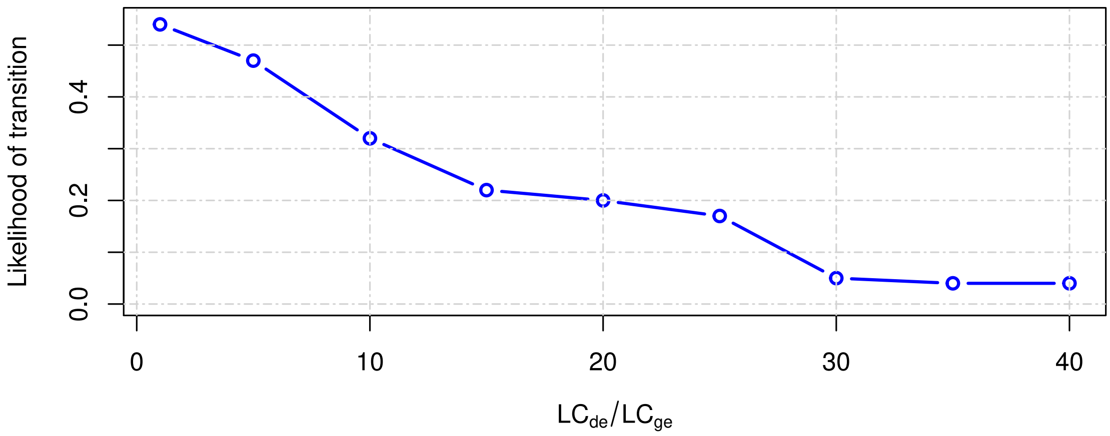


(b) Output growth - Aggregate shocks.

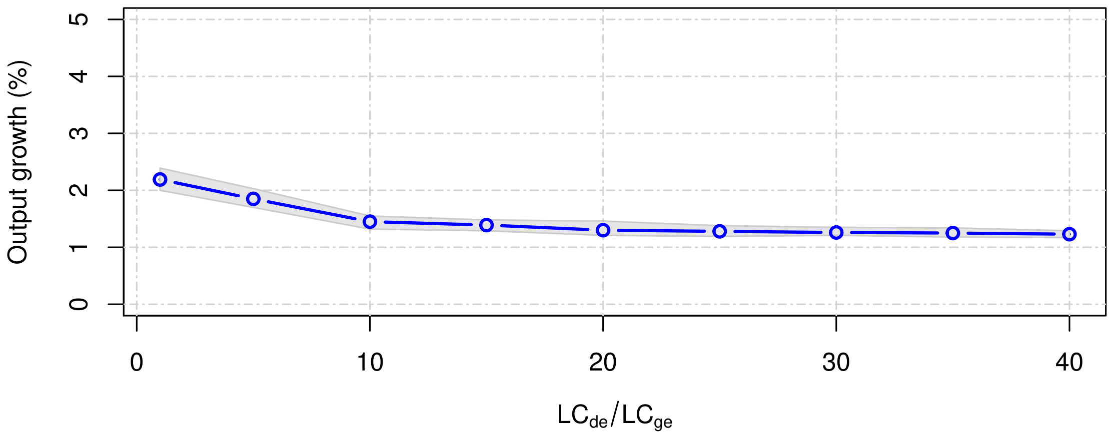


(c) Emissions growth - Aggregate shocks.

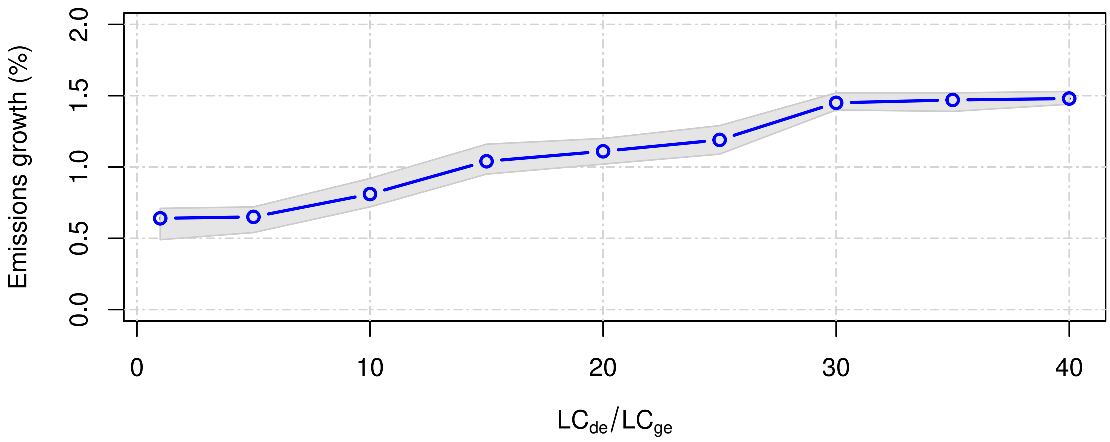
Figure 5: Likelihood of transition, average output and emissions growth under different policy strengths and individual climate damages targeting labour productivity. LC_{de}/LC_{ge} represents the relative cost-advantage of brown energy technologies at the beginning of the simulation; 20% is the baseline. MC of size 200 is used, shaded area represents 90% percentile interval.



(a) Likelihood of transition - Individual shocks to labour productivity.

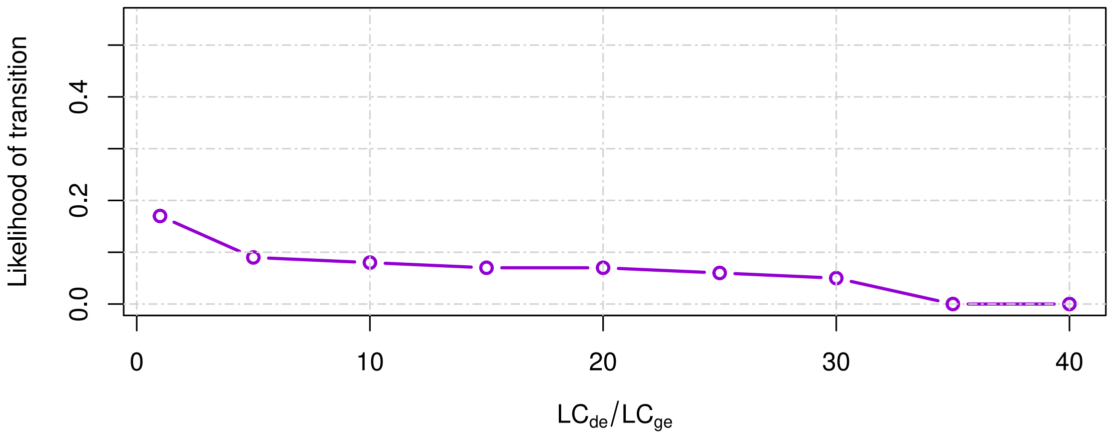


(b) Output growth - Individual shocks to labour productivity.

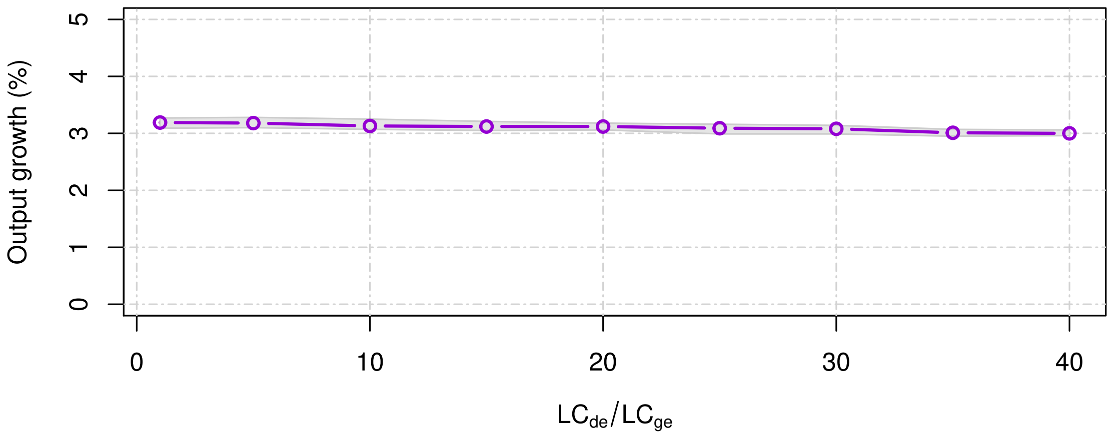


(c) Emissions growth - Individual shocks to labour productivity.

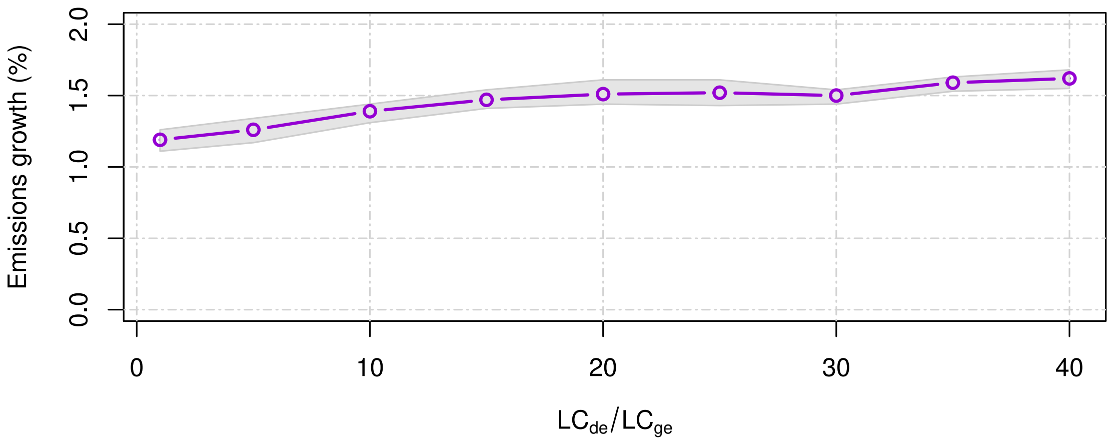
Figure 6: Likelihood of transition, average output and emissions growth under different policy strengths and individual climate damages targeting energy efficiency. LC_{de}/LC_{ge} represents the relative cost-advantage of brown energy technologies at the beginning of the simulation; 20% is the baseline. MC of size 200 is used, shaded area represents 90% percentile interval.



(a) Likelihood of transition - Individual shocks to energy efficiency.



(b) Output growth - Individual shocks to energy efficiency.



(c) Emissions growth - Individual shocks to energy efficiency.

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A Appendix - Model details

The capital good industry

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 represent the technical features of the machine produced, and $B^k_{i,\tau}$, which represent the features of the production technique employed by firm i, with τ being the technology vintage. 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, energy efficiency and, eventually, a carbon tax. 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 $\vartheta_i^{in}(t) = 1 - \exp^{-\varsigma_1 INNOV_i(t)}$ 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 new technology whose main features are described by equations (**??**), (**??**) and (**??**) in section **??**. 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, as specified by equation (**??**). 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, $NC_i(t)$[28] consumption-good firms thus have access to imperfect information about the available machines.

The consumption good industry

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_j^d depends upon adaptive expectations $D_j^e = f[D_j(t-1), D_j(t-2), ..., D_j(t-h)]$, desired inventories ($N_j^d$), and the actual stock of inventories (N_j):

$$Q_j(t)^d = D_j^e(t) + N_j^d(t) - N_j(t), \tag{25}$$

where $N_j(t) = \iota D_j^e(t),\ \iota \in [0,1]$.

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):[29]

$$EI_j^d(t) = K_j^d(t) - K_j(t). \tag{26}$$

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 according to (**??**) . Total replacement investment is then computed at firm level as the number of scrapped machines satisfying the previous condition, 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 as expressed by equation (**??**). Consumers have imperfect information regarding the final product (see Rotemberg, 2008 , for a survey on consumers' imperfect price knowledge) which 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 $l_j(t)$:

$$E_j(t) = -\omega_1 p_j(t) - \omega_2 I_j(t), \tag{27}$$

where $w_{1,2} \geq 0$.[30] 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:

$$f_j(t) = f_{j,t-1}\left(1 + \chi \frac{E_j(t) - \bar{E}_t}{\bar{E}_t}\right), \tag{28}$$

[28]The random sample of new customers is proportional to the size of $HC_i(t)$. In particular, $NC_i(t) = \Upsilon HC_i(t)$, with $0 \leq \Upsilon \leq 1$.

[29]In line with the empirical literature on firm investment behaviour (Doms and Dunne, 1998), firms' expansion in production capacity is limited by a fixed maximum threshold. Moreover, as described below, credit-constrained firms' effective investment does not reach the desired level.

[30]Such unfilled demand is due to the difference between expected and actual demand. Firms set their production according to the expected demand. If a firms is not able to satisfy the actual demand, its competitiveness is accordingly reduced. On the contrary, if expected demand is higher than actual one, inventories accumulate.

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

The banking industry, complements.

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

$$c_j(t)Q_j(t) + EI_j(t)^d + RI_j(t)^d \leq NW_j(t)^d + Deb_j(t)^d \tag{29}$$

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 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 $k > 0$:

$$MTC_t = k \sum_{j=1}^{N} NW_{j,t-1}. \tag{30}$$

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 firms is fulfilled and there are no credit-rationed firms. It follows that in any period the stock of loans of the bank satisfies the following constraint:

$$\sum_{j=1}^{N} Deb_j(t) = Loan(t) \leq MTC_t. \tag{31}$$

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.

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:

$$w(t) = w(t-1)\left[1 + \psi_1 \frac{\Delta \bar{AB}(t)}{\bar{AB}(t-1)} + \psi_2 \frac{\Delta cpi(t)}{cpi(t-1)} + \psi_3 \frac{\Delta U(t)}{U(t-1)}\right], \tag{32}$$

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 and worker wages (or on profits only) and pays to unemployed workers a subsidy, which corresponds to a fraction of the current market wage. In fact, taxes 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 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 that in turn coincides with the sum of aggregate consumption, investment ($I_t = EI_t + RI_t$) and change in inventories (ΔN):

$$\sum_{i=1} Q_i(t) + \sum_j Q_j(t) = Y_t \equiv C_t + I_t + \Delta N. \quad (33)$$

Climate module: carbon cycle and time-line of events

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:

$$NPP(t) = NPP(0)\left(1 + \beta_C \log \frac{C_a(t)}{C_a(0)}\right)(1 - \beta_{T_1} T_m(t-1)) \quad (34)$$

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, 1990; Allen and Amthor, 1995; Matthews, 2007), and β_{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.[31]

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).[32] 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:

$$C_m(t) = C_m^*(t)\left[\frac{C_a(t)}{C_a(0)}\right]^{\frac{1}{\xi(t)}} \quad (35)$$

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.[33] The Revelle rises with atmospheric CO_2 (Goudriaan and Ketner, 1984; Rotmans, 1990) implying that the oceans' marginal capacity to uptake carbon fall as its concentration in the atmosphere increases. Moreover, rising temperatures 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 equations (18) and (19) in the main text, and mediated by the accumulation of carbon leads to global warming through increasing radiative forcing according to a logarithmic relationship:

$$F_{CO_2}(t) = \gamma \log\left(\frac{C_a(t)}{C_a(0)}\right). \quad (36)$$

Equation (36) 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.

[31] Even if the role of climate change on biosphere's carbon uptake of is still object of debate (Shaver et al., 2000; Chiang et al., 2008; IPCC, 2001, ch. 3), the recent IPCC (2007a) provides evidences of stronger positive climate-carbon cycle feedbacks.

[32] In particular, it is composed by a 100 meters mixed layer (which constitutes upper oceans) and a deep layer of 3700 meters for an average total depth of 3800 meters. Our representation of the oceans resembles that in Nordhaus (1992).

[33] The Revelle factor (Revelle and Suess, 1957) expresses the absorption resistance of atmospheric carbon dioxide by the ocean surface layer. The capacity of the ocean waters to take up surplus CO_2 is inversely proportional to its value.

B Appendix - Parameters' value

Table 8: Main parameters and initial conditions in the economic system. For previous parametrization of some sub-portions of the model and for model sensitivity to key parameters see Dosi et al. (2006, 2010, 2013).

Description	Symbol	Value
Monte Carlo replications	MC	200
Time sample in economic system	T	400
Time sample in climate system	T	400
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	$\bar{\mu}_0$	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	ψ_1	1
Wage setting Δcpi weight	ψ_2	0
Wage setting ΔU weight	ψ_3	0
R&D investment propensity (industrial)	ν	0.04
R&D allocation to innovative search	ξ	0.5
Firm search capabilities parameters	$\zeta_{1,2}$	0.3
R&D investment propensity (energy)	ξ_e	0.01
Share of energy sales spent in R&D	v_e	0.01
Beta distribution parameters (innovation)	(α_1, β_1)	$(3, 3)$
Beta distribution support (innovation)	$[\chi_1, \bar{\chi}_1]$	$[-0.15, 0.15]$
New customer sample parameter	$\bar{\omega}$	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
Initial (2000) share of green energy		0.1

Table 9: Climate box main parameters and initial conditions.

Parameter	**Symbol**	**Value**	**Unit of Measurement**	**Source**
Preindustrial Global Mean Surface Temp.	T_{pre}	14	degree Celsius	Sterman et al. (2013)
Preindustrial carbon in the ocean (per meter)		10.237	GtonC	Sterman et al. (2013)
Preindustrial reference CO_2 in atmosphere	Ca_0	590	GtonC	Sterman et al. (2013)
Preindustrial Net Primary Production	NPP_{pre}	85.177	GtonC/year	Goudriaan and Ketner (1984)
Initial carbon in the atmosphere		830.000	GtonC	Nordhaus and Sztorc (2013)
Initial carbon in deep oceans		10,010.000	GtonC	Nordhaus and Sztorc (2013)
Initial temperature in atmosphere	T_0	14.800	degree Celsius	Nordhaus and Sztorc (2013)
Response of primary production to carbon conc.	β_C	1	Dmnl	Goudriaan and Ketner (1984)
Reference buffer factor	revelle	9.7	Dmnl	Goudriaan and Ketner (1984)
Index for response of buffer factor to carbon conc.	deltaC	3.92	Dmnl	Goudriaan and Ketner (1984)
Eddy diffusion coefficient for circulation in oceans	d_{eddy}	1	Dmnl	Oeschger et al. (1975)
Mixed oceans depth	d_{mixed}	100	m	Oeschger et al. (1975)
Deep oceans depth	d_{deep}	3500	m	Sterman et al. (2013)
Sensitivity of carbon uptake to temperature by land	β_{TC}	-0.01	1/degree Celsius	Friedlingstein et al. (2006)
Sensitivity of carbon uptake to temperature	β_T	0.003	1/degree Celsius	Friedlingstein et al. (2006)
Diffusion for atmospheric temperature equation	c_1	0.098		Nordhaus and Sztorc (2013)
Equilibrium climate sensitivity	λ	2.9	degree Celsius	Nordhaus and Sztorc (2013)
Diffusion in deep oceans temp. equation	c_3	0.088		Nordhaus and Sztorc (2013)
Sensitivity of atmospheric temp. to deep ocean temp.	c_4	0.025		Nordhaus and Sztorc (2013)
Radiative forcing coefficient	γ	5.35	W/m2	Sterman et al. (2013)
GtC to $GtCO_2$ conversion factor		3.67		IPCC (2001)
		Climate Shocks		
Sensitivity to location	a_0	4		authors
Sensitivity to scale	b_0	100		authors

C Appendix - Tests for statistical equilibrium and ergodicity

This section largely draws on Guerini and Moneta (2017). Assume that a simulation model is used to produce synthetic series X_k for a set of variables $k = 1, ..., K$. In particular M Monte Carlo realizations, each of length T simulation periods are collected. Then, one can test that the series, or a transformation of them, have distributional properties that are time-independent; and that they are, ergodic, meaning that the stochastic process underlying the observed time series can be treated as a random sample. These two assumptions can be tested through a simple procedure. Indeed if we consider all the M time series realization of a variable k of interest we will collect a matrix with dimensions $M \times T$ containing all the observations $X^m_{k,t}$, where m indicates the number of the MC run and t the simulation time. We here define *ensembles* all the possible column vectors of such a matrix; therefore, each of these vectors contains the M observations $X^m_{k,\cdot}$ with $m = 1, ..., M$, in which the time dimension is fixed; we instead define *samples* all the possible row vectors of such a matrix, each of which contains the T observations $Y^{\cdot}_{k,t}$ with $t = 1, ..., T$ in which the Monte Carlo dimension is fixed. Hence, denoting by $F_t(X_k)$ the empirical cumulative distribution function of an ensemble and by $F_m(X_k)$ the empirical cumulative distribution function of a sample, testing for statistical equilibrium and for ergodicity reduces to test respectively for the following conditions using the Kolmogorov-Smirnov statistic:

$$F_i(X_k) = F_j(X_k) \quad \forall i, j \in \{1, ..., T\} \tag{37}$$

$$F_h(X_k) = F_g(X_k) \quad \forall h \in \{1, ..., T\},\ g \in \{1, ..., M\}. \tag{38}$$

Therefore, we performed two kind of tests as represented in Figure 7: we recursively run tests of pairwise equality of distributions and we presented the percentage of non-rejection of such tests. Rejecting the test would imply that the distributions under investigation are different one from the other. For the model to be in an ergodic statistical equilibrium, we need to have high percentages of non-rejection, meaning that we cannot distinguish between distributions. In case this is not verified, MC runs can be clustered and, then, the same procedure will be applied to any cluster. If we register high percentages of non-rejection within each cluster we can claim these clusters represent multiple statistical equilibria. Finally, if some summary statistics of model behaviour exhibit distributions that are statistically different across clusters, we claim that statistical equilibria are truly different one from the other.

Figure 7: Diagram showing the elements of comparison when testing for statistical equilibrium (left) and for ergodicity (right). Source: Guerini and Moneta (2017).

$$X^k = \begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,T} \\ x_{2,1} & \cdots & \cdots & x_{2,T} \\ \vdots & \vdots & \vdots & \vdots \\ x_{M,1} & x_{M,2} & \cdots & x_{M,T} \end{pmatrix} \qquad X^k = \begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,T} \\ x_{2,1} & \cdots & \cdots & x_{2,T} \\ \vdots & \vdots & \vdots & \vdots \\ x_{M,1} & x_{M,2} & \cdots & x_{M,T} \end{pmatrix}$$