

Working Paper

Faraway, so Close: Coupled Climate and Economic Dynamics in an Agent-Based Integrated Assessment Model

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Abstract

In this paper we develop the first *agent-based integrated assessment model*, which offers an alternative to standard, computable general-equilibrium frameworks. The *Dystopian Schumpeter meeting Keynes* (DSK) model is composed of heterogeneous firms belonging to capital-good, consumption-good and energy sectors. Production and energy generation lead to greenhouse gas emissions, which affect temperature dynamics in a non-linear way. Increasing temperature triggers climate damages hitting, at the micro-level, workers' labor productivity, energy efficiency, capital stock and inventories of firms. In that, aggregate damages are emerging properties of the out-of-equilibrium interactions among heterogeneous and boundedly rational agents. We find the DSK model is able to account for a wide ensemble of micro and macro empirical regularities concerning both economic and climate dynamics. Moreover, different types of shocks have heterogeneous impact on output growth, unemployment rate, and the likelihood of economic crises. Finally, we show that the magnitude and the uncertainty associated to climate change impacts increase over time, and that climate damages are much larger than those estimated through standard IAMs. Our results point to the presence of tipping points and irreversible trajectories, thereby suggesting the need of urgent policy interventions.

Keywords: Climate Change; Agent-Based Models; Integrated Assessment; Macroeconomic Dynamics; Climate Damages.

JEL: C63, Q40, Q50, Q54.

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1 Introduction

This paper presents the first *agent-based integrated assessment model*, comprising a complex evolving economy, populated by heterogeneous, boundedly-rational agents, a climate box, and a stochastic damage generating function endogenously yielding climate shocks of different magnitudes.

The Paris agreement signed by 195 countries at the 2015 United Nations Climate Change Conference constitutes an unprecedented event. It legally binds parties to undertake efforts to keep the global mean surface temperature at the end of the century within the 2 degrees above preindustrial levels, and eventually to achieve the 1.5 degree target. Unfortunately, climate change will significantly impact on our societies and economies even if such ambitious objectives are achieved (Weitzman, 2009; IPCC, 2014; Schleussner et al., 2016) and, in case of failure, the effects will be catastrophic.¹ Accordingly, there is a lively debate on the size of climate damages we may suffer (see e.g. Stern, 2007; IPCC, 2014; Nordhaus, 2014), and on the likelihood and effects of overcoming tipping points in the Earth biophysical system (Greiner et al., 2010; Brook et al., 2013; Grune et al., 2015).²

The impact of climate change and the design of adaptation and mitigation policies is commonly performed in climate economics by relying on integrated assessment models (IAMs),³ which add a simple carbon cycle module to a computable general equilibrium barebone (e.g. Nordhaus, 1992; Tol, 1997; Hope, 2006; Bosetti et al., 2006; Golosov et al., 2014). However, IAMs have been fiercely criticized by an increasing number of scholars for their simplifying assumptions (see Pindyck, 2013; Stern, 2013, 2016; Weitzman, 2013; Revesz et al., 2014; Farmer et al., 2015; Balint et al., 2017, among many contributions). The reason is that IAMs make completely ad-hoc assumptions on the relationship between CO₂ atmospheric concentration and temperature increases, as well as about the damage function linking climate change to socio-economic damages (Pindyck, 2013). As a result, they usually underestimate or neglect the scale of the risks of climate change, which can possibly lead to the emergence of tipping points and non-reversibilities (Stern, 2016). Moreover, IAMs rely on unreasonable assumptions, such as homogenous preferences, rational expectations, inter-temporal optimization, market-clearing and general equilibrium effects in order to determine welfare changes.⁴ Such assumptions are difficult to defend in presence of deep uncertainty characterizing the occurrence of extreme physical events and technical change. In addition, they do not allow to capture the effects of the interactions among heterogeneous, adaptive agents on economic dynamics, and thus prevent the study of the dynamics of income and wealth inequality in relation to climate change and to the possible policy responses.⁵

¹See also Sections 1.3 and 2.3 of the IPCC (2014) for what concerns current and future impacts and the review in Carleton and Hsiang (2016).

²On the latter theme, the literature on early warning indicators has been expanding as well, see Biggs et al. (2009); Brock and Carpenter (2010); Bentley et al. (2014).

³As a possible alternative, Pindyck (2016) is recently proposing to substitute the use of integrated assessment models with statistical analysis of expert opinions of future impacts of climate change.

⁴The assumption of the representative agent is questionable on both theoretical (Kirman, 1992) and empirical (Forni and Lippi, 1997; Heckman, 2001). However, some attempts to include heterogeneity in integrated assessment models is currently under development (Bosetti and Maffezzoli, 2013).

⁵A relevant disclaimer applies. In the present discussion we refer to standard integrated assessment models as those used in the economics literature and pioneered by Nordhaus (1992). These models are mainly concerned with cost-benefit assessments. Differently, main models used within the IPCC exercises, despite being mostly CGE based, are employed to project socio-economic conditions under different scenarios and to assess different mitigation pathways. See Clarke et al. (2009) for an overview of main models and Emmerling et al. (2016) for recent and detailed example.

Given the current impasse, new approaches to modeling the co-evolution of climate change and economic dynamics are needed. Agent-based models (Tesfatsion and Judd, 2006; Fagiolo and Roventini, 2012, 2017) constitute a valuable and promising alternative to IAMs (Smajgl et al., 2011; Farmer et al., 2015; Stern, 2016; Mercure et al., 2016; Balint et al., 2017). Agent-based models consider the real world as a *complex evolving system* (more on this in Farmer and Foley, 2009; Dosi, 2012; Dosi and Virgillito, 2016; Kirman, 2016), wherein the interaction of many heterogeneous agents, possibly across different spatial and temporal scales, gives rise to the emergence of aggregate properties that cannot be derived by the simple aggregation of individual ones. Moreover, agent-based models offer flexible tools to study the evolution of persistently out-of-equilibrium systems, where behaviours that are nearly stable for long time may change dramatically, stochastically, and irreversibly in response to small endogenous shocks (Balint et al., 2017).⁶

A new generation of agent-based models studying the intricate links between economic growth, energy, and climate change at regional, national, and global level has blossomed in the last years (see Gerst et al., 2013; Hasselmann and Kovalevsky, 2013; Wolf et al., 2013; Ponta et al., 2016; Safarzyńska and van den Bergh, 2016 and the survey in Balint et al., 2017).⁷ However, little effort has been devoted to the development of integrated frameworks, wherein the economy and the climate may endogenously interact.

For these reasons, we develop the *Dystopian Schumpeter meeting Keynes* (DSK) model, which is the first attempt to provide a fully-fledged agent-based integrated assessment framework. It builds on Dosi et al. (2010, 2013, 2016) and extends the *Keynes+Schumpeter* (K+S) family of models, which account for endogenous growth, business cycles and crises. The model is composed by heterogeneous firms belonging to a capital-good industry and to a consumption-good sector. Firms are fed by an energy sector, which employ *dirty* or *green* power plants. The production activities of energy and manufacturing firms lead to CO₂ emissions, which increase the Earth surface temperature in a non-linear way as in Sterman et al. (2013). Increasing temperatures trigger micro stochastic climate damages impacting in a heterogeneous way on workers' labour productivity, and on the energy efficiency, capital stock and inventories of firms. The DSK model accounts both for frequent and mild climate shocks and low-probability but extreme climate events. Technical change occurs both in the manufacturing and energy sectors. Innovation determines the cost of energy produced by dirty and green technologies, which, in turn, affect the energy-technology production mix and the total amount of CO₂ emissions. In that, structural change of the economy is intimately linked to the climate dynamics. At the same time, climate shocks affect economic growth, business cycles, technical-change trajectories, green-house gas emissions, and global temperatures.

The DSK model provides the first attempt to link a complex adaptive economy with endogenous technical change, to a climate box characterized by feedback loops and non-linear relationships within the carbon cycle (see Sterman et al., 2012). Moreover, it provides a genuine micro-foundation of climate-related damages. In particular, we introduce a stochastic damage function, where the probability and magnitude of damages evolves according to the behaviour of Earth's average temperature, which in turn is affected by the dynamics of the economic system. A variety of shocks and their combinations are explored, and simulation results are compared to recent results from standard IAMs (Nordhaus, 2014).

Simulation results show that the DSK model is able to replicate a wide array of micro and macro-economic stylized facts and climate-related statistical regularities. Moreover, the exploration of different climate shock scenarios reveals that the impact of climate change on economic performances is substantial, but highly hetero-

⁶The adoption of agent-based integrated assessment model also ease stakeholder participation and scenario plausibility exploration (Moss et al., 2001; Moss, 2002a). Indeed, the higher degree of realism of agent based models (Farmer and Foley, 2009; Farmer et al., 2015; Fagiolo and Roventini, 2017) allows to involve policy makers in the process of the development of the model employed for policy evaluation (Moss, 2002b).

⁷Some interesting attempts at providing mixed system dynamics and agent based frameworks (Monasterolo and Raberto, 2016), as well as stock-flow consistent macro simulation models (Dafermos et al., 2017) are appearing.

geneous, depending on the type of climate damages. More specifically, climate shocks to labour productivity and capital stocks lead to the largest output losses and the highest economic instability, respectively. We also find that the ultimate macroeconomic damages emerging from the aggregation of agent-level shocks are more severe than those obtained by standard IAMs, with the emergence of tipping-points and irreversible catastrophic events.

Our results highlight the role of agents' heterogeneity and interactions in the transmission and magnification of climate shocks across the economy. In that, our results call for urgent of policy interventions to contain the possibly enormous economic losses produced by climate change, which could bring the system towards disasters along the current business-as-usual growth path.

The paper is organized as follows. Section 2 describes the structure of the DSK model. Section 3 illustrates the dynamics generated by the model and its capability to account for economic and climate empirical regularities. In Section 4, we explore a wide range of climate shock scenarios and their impact of economic dynamics. Finally, 5 discusses the results and concludes the paper.

2 The DSK model

The *Dystopian Schumpeter meeting Keynes* (DSK) model couples an economy populated by heterogenous, interacting firms and a climate box. The economy and the climate are linked by multiple, non-linear feedbacks, and co-evolve over time. Figure 1 provides a graphical representation of the model.

The economy builds on the K+S model (Dosi et al., 2010, 2013) and is composed by two vertically separated industries, wherein firms are fed by an energy sector and financed by loans from a bank - if needed. Capital-good firms invest in R&D and innovate to improve the productivity, and possibly the energy-efficiency and environmental friendliness of their machines. Consumption-good firms invest in capital-goods and produce an homogenous product.

Both the energy and industrial sectors emit CO₂, whose concentrations in the atmosphere affect the evolution of the climate. Specifically, we model a carbon cycle characterized by feedback loops linking Earth's radiative forcing and the global mean surface temperature. The effects of an increase in Earth's temperature on the economic system are captured by a stochastic *disaster generating function*. Under a warming climate, the probability of large shocks hitting, e.g. firms' labour productivity or capital stocks, increases together with the mean size of the damage. Therefore, an increase in Earth's surface temperature does not translate automatically in higher aggregate damages as in most IAM, but rather, it modifies the very structure of the economy, thus affecting stochastic process characterizing economic growth. The details on model structure are spelled out in Appendix A.

2.1 Consumption and capital good sectors

The economy comprises a capital-good and a consumption-good sector, which are vertically related by investment in machines.

Firms in the *capital-good industry* produce machine-tools using labour and energy. The technology of the machines of vintage τ is captured by their *labour productivity*, *energy efficiency* and *environmental friendliness* and it is represented by a set of six coefficients $(A_{i,\tau}^k, B_{i,\tau}^k)$, with $k \in \{L, EE, EF\}$. Let us start with labor productivity, L : $A_{i,\tau}^L$ stands for the productivity of the capital-good in the consumption-good industry, while $B_{i,\tau}^L$ is the productivity of the production technique needed to manufacture the machine. The apex EE , instead, refers to energy efficiency: $A_{i,\tau}^{EE}$ represents the output per energy unit obtained by a consumption-good firm using the machine-tool, and $B_{i,\tau}^{EE}$ is the corresponding ratio characterizing the production of the capital-good manufacturer

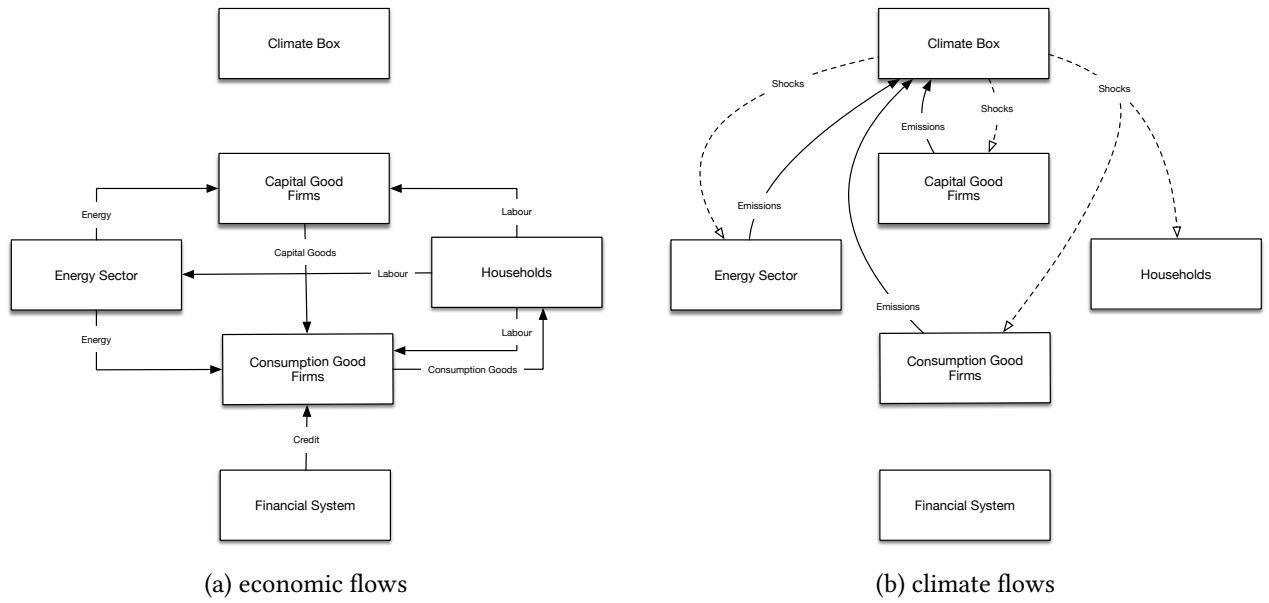


Figure 1: A stylized representation of the DSK model.

technique. Given the monetary wage, $w(t)$, and the cost of energy, $c^{en}(t)$, the unitary cost of production for capital-good firm i is given by:

$$c_i^{cap}(t) = \frac{w(t)}{B_{i,\tau}^L} + \frac{c^{en}(t)}{B_{i,\tau}^{EE}}. \quad (1)$$

Similarly, the unitary production cost of a consumption-good firm j is:

$$c_j^{con}(t) = \frac{w(t)}{A_{i,\tau}^L} + \frac{c^{en}(t)}{A_{i,\tau}^{EE}}. \quad (2)$$

Finally, machines and techniques are characterized by their degree of environmental friendliness (identified by the apex EF), which corresponds to the amount of polluting substances they emit in each period for each unit of energy employed throughout the production process. Pollutants can be of different sources and affect the quality of air, water and ground.⁸ In what follows, we focus only on Greenhouse Gases (GHGs) and, in particular, on CO_2 as it represents the major driver of climate change (IPCC, 2013). Hence, $A_{i,\tau}^{EF}$ refers to the environmental friendliness of the machine-tool, while $A_{i,\tau}^{EF}$ to that of firm i 's production technique.

Firms in the capital-good industry adaptively strive to increase market shares and profits trying to improve their technology via innovation and imitation. They are both costly processes: firms invest in R&D a fraction of their past sales in the attempt to discover new technology or to imitate more advanced competitors. As in Dosi et al. (2010), both innovation and imitation are modelled as two step processes. The first step captures the stochastic nature of technical change and determines whether a firm successfully innovates or imitates through a draw from a Bernoulli distribution, where the (real) amount invested in R&D, that is, ultimately, number of people devoted to search, affects the likelihood of success. The second step determines the size of the technological advance via additional stochastic processes:

$$A_{i,\tau+1}^k = A_{i,\tau}^k(1 + \chi_{A,i}^k) \quad \text{for } k = L, EE \quad (3)$$

$$B_{i,\tau+1}^k = B_{i,\tau}^k(1 + \chi_{B,i}^k) \quad \text{for } k = L, EE, \quad (4)$$

⁸See the website of the US Environmental Protection Agency (EPA) for additional information about specific pollutants, <http://epa.gov>.

$$A_{i,\tau+1}^{EF} = A_{i,\tau}^{EF}(1 - \chi_{A,i}^{EF}) \quad (5)$$

$$B_{i,\tau+1}^{EF} = B_{i,\tau}^{EF}(1 - \chi_{B,i}^{EF}), \quad (6)$$

where $\chi_{A,i}^k$ and $\chi_{B,i}^k$ are independent draws from $Beta(\alpha^k, \beta^k)$ distributions over the supports $[\underline{x}^k, \bar{x}^k]$, respectively for $k \in \{L, EE, EF\}$. The support of each distribution defines the potential size of the technological opportunity (Dosi, 1988) along the corresponding dimension. Specifically, in case of successful innovation, the new vintage of capital-goods will be characterized by a novel combination of labour productivity, energy-efficiency and environmental friendliness (i.e. amount of pollutants per unit of energy used in the production process, see equations 5 and 6). Finally, successful imitators have the opportunity to copy the technology of the closest competitors in the technological space.

Firms in the *consumption-good industry* produce a homogeneous good using their stock of machines, energy and labour under constant returns to scale. Their demand comes from the consumption expenditures of workers. Firms plan their production according to (adaptive) demand expectations,⁹ desired inventories, and their stock of inventories. Whenever the capital stock is not sufficient to produce the desired amount, firms invest in order to expand their production capacity.

Firms also invest to replace current machines with more technologically advanced ones. In particular, given $\Xi_i(t)$, the set of all vintages of machines owned by firm j at time t , the machine of vintage τ is replaced with a new one if

$$\frac{p^{new}}{c_j^{con}(t) - c^{new}} = \frac{p^{new}}{\left[\frac{w(t)}{A_{i,\tau}^L} + \frac{c_j^{en}(t)}{A_{i,\tau}^{EE}} \right] - c_j^{new}} \leq b \quad (7)$$

where p^{new} and c^{new} are the price and unitary cost of production associated to the new machine and b is a pay-back parameter determining firms' "patience" in obtaining net returns on their investments.¹⁰ Gross investment of each firm is the sum of expansion and replacement investments. Aggregate investment just sums over the investments of all consumption good firms.

Labour productivities, energy consumption and emissions in the consumption-good industry evolve according to the technology embedded in the capital stock of each firm. Consumption-good firms choose their capital-good supplier comparing price, productivity, and energy efficiency of the currently manufactured machine tools they are aware of. Indeed, as the capital-good market is characterized by imperfect information, consumption-good firms can directly buy from a subset of machine-tool producers. Machine production is a time-consuming process: consumption-good firms receive the ordered machines at the end of the period. Pricing follows a variable mark up rule.¹¹

Consumption-good firms must finance their investments as well as their production. In line with a large body of literature (Stiglitz and Weiss, 1981; Greenwald and Stiglitz, 1993) we assume imperfect credit markets. Firms first employ their cash stock, and if the latter does not fully cover total production and investment costs, they borrow external funds from a bank. More precisely, we assume that each firm deposits its net cash flows at the bank and, if it falls short of that, it can get access to an overdraft credit line. The bank sets the maximum amount of credit as a multiple of firms' deposits and it allocates them to borrowers on a pecking-order basis according to the ratio between net worth and sales (see Dosi et al., 2013).¹² Total credit demand by firms can

⁹In the benchmark setup, expectations are myopic. The results are robust for different expectation setups. More on that in Dosi et al. (2006) and Dosi et al. (2017a).

¹⁰This is in line with a large body of empirical analyses showing that replacement investment is typically not proportional to the capital stock (e.g. Feldstein and Foot, 1971; Eisner, 1972; Goolsbee, 1998).

¹¹These assumptions finds all in line with large bodies of literature; see, e.g., Rotemberg (2008) for details on pricing, imperfect information and behavioural attitudes of consumers and Boca et al. (2008) for presence of gestation lag effects in firms' investments.

¹²Notice that firms' deposits constitute the only "debt" of the bank in the model. Accordingly, the rule for the determination of maximum credit is equivalent to one where the bank sets credit supply in order not to violate a desired target on the debt-to-asset ratio.

be higher than the maximum supply of credit, in which case credit rationing arises.¹³

Firms sets the price of their final good applying a variable mark-up (μ_j) on their unit cost of production:

$$p_j^{con}(t) = c_j^{con}(t)[1 + \mu_j(t)]. \quad (8)$$

The mark-up change over time according to the evolution of firm's market share, f_j (in line with a lot of evolutionary literature and also with "customer market" models originally described by Phelps and Winter, 1970):

$$\mu_j(t) = \mu_j(t-1) \left[1 + v \frac{f_j(t-1) - f_j(t-2)}{f_j(t-2)} \right] \quad (9)$$

with $0 \leq v \leq 1$.

Also the consumption-good market is characterized by imperfect information (see Rotemberg, 2008, for a survey on consumers' imperfect price knowledge). As a consequence, consumers cannot instantaneously switch to the most competitive producer even if the good is homogenous. In turn, market shares evolve according to a "quasi replicator" dynamics: more competitive firms expand while firms with a relatively lower competitiveness level shrink. The competitiveness of firms depends on price as well as on unfilled demand.

At the end of every period, capital- and consumption-good firms compute their profits, pay taxes, and update their stock of liquid assets. A firm exits the market if its stock of liquid assets is negative or if its market share falls to zero. As the number of firms is fixed over time, each dead firm is replaced by a new entrant.¹⁴

2.2 The energy industry

Energy production is performed by a profit-seeking, vertically-integrated monopolist through power plants embodying *green* and *dirty* technologies.¹⁵ The energy monopolist produces on demand $D_e(t)$ units of electricity for firms in the capital-good and consumption-good industries (we exclude the possibility of energy blackouts). The profits of the energy producer are equal to:

$$\Pi_e(t) = p_e(t)D_e(t) - PC_e(t) - IC_e(t) - RD_e(t), \quad (10)$$

where $p_e(t)$ is energy price, $PC_e(t)$ is the total cost of generating an amount $D_e(t)$ of energy, $IC_e(t)$ denotes expansion and replacement investments, $RD_e(t)$ is the R&D expenditure. In the next sections, we explain in details the elements in equation 10.

2.2.1 Electricity producing technologies, costs and revenues

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

¹³Finally, also the firms that are not credit rationed face limits in the utilization of their overdraft credit. The ratio between a firm's debt and its sales cannot exceed a maximum threshold that depends on the firm's past sales (see Dosi et al., 2013, for more details)

¹⁴Furthermore, in line with the empirical literature on firm entry (Caves, 1998), we assume that entrants are on average smaller capital and stock of liquid assets than incumbents.

¹⁵The assumption of monopolistic production may sound questionable in light of the liberalization process at work in the energy markets, but it is worth noting that oligopolistic liberalized electricity markets are prone to tacit collusion rooted in repeated interaction, tall entry barriers, and a relatively high degree of transparency in supply offers (see e.g. Fabra and Toro, 2005).

for a dirty plant of vintage τ is given by

$$c_{de}(\tau, t) = \frac{p_f(t)}{A_{de}^\tau} \quad (11)$$

where $p_f(t)$ is the price of fossil fuels, exogenously determined on international markets.¹⁶ The dirty technology leaves a carbon footprint, in that burning fossil fuels yields em_{de}^τ emissions per energy unit.

As the electricity production is a highly capital-intensive process, which mainly requires power generation assets and resources, we assume away labour from electricity production. The total production cost depends on which plants are used. As the marginal cost of electricity production of green plants is null, the monopolist will employ them first and it will switch on the dirty plants only if the green capacity is insufficient to satisfy demand. Even in that case, the cheapest dirty plants will be used first.¹⁷

Let IM be the set of infra-marginal power plants, whose total production equals demand. If $D_e(t) \leq K_{ge}(t)$, IM only includes green plants and the total production cost is zero. If $D_e(t) > K_{ge}(t)$, the total energy production cost (PC_e) is positive as dirty power plants are activated:

$$PC_e(t) = \sum_{\tau \in IM} g_{de}(\tau, t) c_{de}(\tau, t) A_{de}^\tau, \quad (12)$$

where $g_{de}(\tau, t)$ is the absolute frequency of vintage τ plants.

The energy producer adds a fixed markup $\mu_e \geq 0$ on the average cost of the most expensive infra-marginal plant. Hence the selling price reads:

$$p_e(t) = \begin{cases} \mu_e & \text{if } D_e(t) \leq K_{ge}(t) \\ \bar{c}_{de}(\tau, t) + \mu_e & \text{if } D_e(t) > K_{ge}(t) \end{cases}, \quad (13)$$

where $\bar{c}_{de}(\tau, t) = \max_{\tau \in IM} c_{de}(\tau, t)$. Note that according to equation 13, the energy producer gains a positive net revenue on all infra-marginal plants.¹⁸

2.2.2 Energy plant investment

The energy producing firm needs to replace obsolete plants, as well as to perform expansion investments whenever the current capacity is insufficient to cover demand. New plants are built in house, but the costs of building new green and dirty plants differ. More specifically, we normalize to zero the costs of building new dirty plants, whereas a cost of IC_{ge}^τ must be sustained in order to install a new green plant.

The capacity stock $K_e(t)$ is defined as the sum of the capacities of all power plants across technologies (green, dirty) and vintages. As the capacities of individual plants are normalized to one, the capacity stock reads:

$$K_e(t) = \sum_{\tau} g_{de}(\tau, t) + \sum_{\tau} g_{ge}(\tau, t), \quad (14)$$

where $g_{de}(\tau, t)$ denotes the absolute frequency of vintage- τ dirty plants, and $g_{ge}(\tau, t)$ is the same for green plants. Given that green power plants produce at full capacity and dirty plants are characterized by thermal

¹⁶The markets for fossil fuels are globally integrated and the prices of different fuels are linked, as also shown by the evidence of co-integration of their time series. Recently, the shale gas revolution has blurred this relationship (Caporin and Fontini, 2016). However, in presence of institutional factors, such as prices indexed on baskets of energy goods, we can consider fossil fuels as homogeneous in their impacts on electricity production costs.

¹⁷Such a merit order rule is based on the actual functioning of the electricity industry. Even before liberalization, the traditional goal of energy systems management was the minimization of system-wide electricity production, transmission, and distribution costs.

¹⁸Other empirically observed ways of exploiting market power include withholding relatively cheap plants and causing network congestion. We think that modeling market power through markups captures all these practices. Note also that a monopolistic producer could arbitrarily increase the price beyond any limit, but this usually does not occur as producers fear regulatory intervention, wish to discourage entry, or there is a price cap set by the regulatory agency.

efficiencies A_{de}^τ , the maximum production level that can be obtained with the available capacity stock is

$$\bar{Q}_e(t) = \sum_{\tau} g_{de}(\tau, t) A_{de}^\tau + \sum_{\tau} g_{ge}(\tau, t). \quad (15)$$

Whenever the maximum electricity production level $\bar{Q}_e(t)$ falls short of the electricity demand $D_e(t)$, the monopolist invests (EI_e^d) to expand the capital stock:

$$EI_e^d(t) = \begin{cases} K_e^d(t) - K_e(t) & \text{if } \bar{Q}_e(t) < D_e(t) \\ 0 & \text{if } \bar{Q}_e(t) \geq D_e(t) \end{cases}. \quad (16)$$

The energy producers employ a payback period routine to choose the technology of its expansion investment. More specifically, the expansion investment involves only new green capacity, whenever the fixed cost of building the cheapest vintage of green plants (\underline{IC}_{ge}) is below the discounted production cost of the cheapest dirty plant (\underline{c}_{de}):

$$\underline{IC}_{ge} \leq b_e \underline{c}_{de}$$

where b_e is a discount factor, $\underline{IC}_{ge} = \min_{\tau} IC_{ge}^\tau$, and $\underline{c}_{de} = \min_{\tau} c_{de}^\tau$. If so, the producer builds $EI_e^d(t)$ units of new green capacity and the expansion investment cost amounts to

$$EC_e(t) = \underline{IC}_{ge} EI_e^d(t) \quad (17)$$

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

2.2.3 R&D expenditures and outcomes

The energy producer tries to innovate in order to discover new green and dirty technologies. The R&D investment is a fraction $v_e \in (0, 1)$ of previous period sales:

$$RD_e(t) = v_e S_e(t-1) \quad (18)$$

The R&D budget is split among green (IN_{ge}) and dirty (IN_{de}) technologies according to the following rule:

$$IN_{ge}(t) = \xi_e RD_e(t) \quad IN_{de}(t) = (1 - \xi_e) RD_e(t),$$

with $\xi_e \in (0, 1)$. Given the R&D investment, the innovative search in the green and dirty technological trajectories is successful with probabilities $\theta_{ge}(t)$ and $\theta_{de}(t)$:

$$\theta_{ge}(t) = 1 - e^{-\eta_{ge} IN_{ge}(t)} \quad \theta_{de}(t) = 1 - e^{-\eta_{de} IN_{de}(t)} \quad (19)$$

with $\eta_{ge} \in (0, 1)$, $\eta_{de} \in (0, 1)$.

Successful innovation in the green technology reduces the fixed costs, thus encouraging the installment of green plants.¹⁹ Formally, the installment cost of a new vintage of green plants, IC_{ge}^τ , is lowered by a factor

¹⁹In real world, the thermal efficiencies of green technologies is far below 100% and there can be efficiency-improving innovations. As higher thermal efficiency allows a faster amortization of the fixed construction cost, we think that our modeling choice yields the same effects (lower fixed construction costs reduce the break-even point) in a more parsimonious setting.

$x_{ge} \in (0, 1)$ (a random draw from a Beta distribution) with respect to the previous vintage:

$$IC_{ge}^\tau = IC_{ge}^{\tau-1} x_{ge} \quad (20)$$

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

$$A_{de}^\tau = A_{de}^{\tau-1}(1 + x_{de}^A) \quad em_{de}^\tau = em_{de}^{\tau-1}(1 - x_{de}^{em}) \quad (21)$$

where x_{de}^A and x_{de}^{em} are independent random draws from a Beta distribution. Note that the new dirty technology could also be characterized by higher thermal efficiency but higher levels of emissions.

2.3 The climate box

The climate box links CO₂ emissions with atmospheric carbon concentrations and the dynamics of Earth's mean surface temperature. Such relationships are modeled through a core carbon cycle as in [Sterman et al. \(2012, 2013\)](#). The climate box captures the major features of the physical and chemical relations governing climate change, paying particular attention to the feedbacks that might give rise to non-linear dynamics, while avoiding a complex and detailed description of the climatic process. Note that such feedbacks are generally overlooked by standard climate-economy models, even though there is ample evidence of their importance in accelerating global warming ([Cox et al., 2000](#)).²⁰

2.3.1 The carbon cycle

Our carbon cycle is modelled as a one-dimensional compartment box based on [Goudriaan and Ketner \(1984\)](#) and [Oeschger et al. \(1975\)](#). On the one hand, atmospheric CO₂ is determined in each period by the interplay of anthropogenic emissions, exchanges with the oceans, and natural emissions from the biosphere. On the other hand, CO₂ is removed from the atmosphere as it is dissolved in the oceans and taken up by biomass through net primary production. To simplify, we model the biosphere as an aggregate stock of biomass endowed with a first order kinetics.

Net primary production (NPP), modeled here as the flux of carbon from the atmosphere to biomass, grows logarithmically with the CO₂ stock ([Wullschlegel et al., 1995](#)) and it is negatively affected by temperature's increase:

$$NPP(t) = NPP(0) \left(1 + \beta_C \log \frac{C_a(t)}{C_a(0)} \right) (1 - \beta_{T_1} T_m(t - 1)), \quad (22)$$

where $C_a(t)$ represents the stock of carbon in the atmosphere at time t , 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 CO₂ fertilization feedback,²¹ while β_{T_1} captures the magnitude of the temperature effect on NPP. A negative relationship between NPP and surface temperature is included to account for such an important climate-carbon feedback. Note that in line with recent findings ([Zhao and Running, 2010](#)), the second term of equation 22 captures the negative impact of global warming on the biosphere uptake, which gives rise to positive climate-carbon cycle feedbacks

²⁰Our modelling effort give rise to a structure that can be categorized in between so-called Simple Climate Models ([Harvey et al., 1997](#), for a review) and Earth-system Models of Intermediate Complexity ([Claussen et al., 2002](#), for a review).

²¹The fertilization feedback refers to the phenomenon of increasing biosphere's carbon uptake due to the stimulus that CO₂ atmospheric concentrations exerts on vegetation productivity ([Allen, 1990](#); [Allen and Amthor, 1995](#); [Matthews, 2007](#)).

(Serman et al., 2012).²²

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).²³ 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. 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:

$$C_m(t) = C_m^*(t) \left[\frac{C_a(t)}{C_a(0)} \right]^{1/\xi(t)} \quad (23)$$

where C_m^* is the reference carbon concentration in the mixed layer, $C_a(t)$ and $C_a(0)$ are respectively the concentrations of atmospheric carbon at time t and at the initial point of the simulation, and ξ is the buffer (or Revelle) factor.²⁴

The Revelle factor is not constant and rises with atmospheric CO_2 (Goudriaan and Ketner, 1984; Rotmans, 1990) implying that the oceans' marginal capacity to uptake carbon diminishes as its concentration in the atmosphere increases:

$$\xi(t) = \xi_0 + \delta \log \left[\frac{C_a(t-1)}{C_a(0)} \right] \quad (24)$$

where ξ_0 is the initial value of the Revelle factor, and $\delta > 0$ expresses the sensitivity of ξ to the relative atmospheric concentration of carbon.

The reference carbon concentration in the mixed layer (C_m^*) is affected by the negative effect of global warming on the seawater solubility of CO_2 (Fung, 1993; Sarmiento et al., 1998), which, in turn accelerates climate change (Cox et al., 2000). As in the previous case, we approximate this feedback to a first order term:

$$C_m^*(t) = C_m(0)[1 - \beta_{T_2} T_m(t-1)] \quad (25)$$

where $C_m(0)$ is the initial concentration of carbon in the mixed layer of the oceans, and β_{T_2} models the sensitivity to temperature changes of the equilibrium carbon concentration in seawater.

Net flux of carbon through the oceans is determined by the relative concentrations of carbon in the two layers. In particular, the net flux from the mixed to the deep layer (ΔC_{md}), is defined by:

$$\Delta C_{md}(t) = k_{eddy} \frac{\left[\frac{C_m(t-1)}{d_m} - \frac{C_d(t-1)}{d_d} \right]}{\bar{d}_{md}} \quad (26)$$

where d_d and d_m are respectively the thickness of deep and mixed layers, \bar{d}_{md} is the mean thickness of the mixed and deep oceans, and k_{eddy} is the eddy diffusion parameter. The flux of carbon through the atmosphere, biosphere and oceans affects the heat transfer across the system and, hence, the dynamics of Earth's surface mean temperature.

²²The role of warming on the biosphere uptake of carbon is still debated and strongly depends on local conditions (Shaver et al., 2000; Chiang et al., 2008; IPCC, 2001, ch. 3). However, the IPCC (2007b) reports evidences of stronger positive climate-carbon cycle feedbacks than previously thought, which would increase future estimates of CO_2 concentrations in the atmosphere.

²³Our representation of the oceans resembles that in Nordhaus (1992). The eddy diffusion refers to any diffusion process by which substances are mixed in a fluid as a result of a turbulent flow. A simplifying example consists in the diffusion of a dissolved sugar molecule across a coffee cup due to the eddies generated by the movements of the spoon.

²⁴The 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.

2.3.2 Global warming

Once carbon exchanges among the atmosphere, the oceans and the biomass reach a new equilibrium, the updated concentrations of carbon affect global warming mainly via radiative forcing. In particular, the global mean surface temperature is determined by the heat content of the surface and mixed layer of the oceans, which are aggregated into a single compartment. We model the behavior of temperatures in the different layers building on [Schneider and Thompson \(1981\)](#) and [Nordhaus \(1992\)](#). The heat content of the different layers is modulated by their reciprocal exchanges and, with respect to the upper compartment (atmosphere and surface oceans), by the CO₂ radiative forcing (F_{CO_2}).²⁵ Therefore, the dynamics of the temperature in the mixed (T_m) and deep (T_d) layers can be modelled as follows:

$$T_m(t) = T_m(t-1) + c_1 \{ F_{CO_2}(t) - \lambda T_m(t-1) - c_3 [T_m(t-1) - T_d(t-1)] \} \quad (27)$$

$$T_d(t) = T_d(t-1) + c_4 \{ \sigma_{md} [T_m(t-1) - T_d(t-1)] \} \quad (28)$$

where temperature (T) is expressed as to pre-industrial levels, R_m and R_d are the thermal inertias in the two layers, λ is a climate feedback parameter, F_{CO_2} represents the radiative forcing in the atmosphere from GHG (relative to pre-industrial levels) and σ_{md} is a transfer rate of water from the upper to lower oceans accounting also for the heat capacity of water. The main climate variable we are interested in is the temperature of the surface-upper oceans compartment, T_m .

Accumulation of GHG leads to global warming through increasing radiative forcing (F_{CO_2}) according to:

$$F_{CO_2}(t) = \gamma \log \left(\frac{C_a(t)}{C_a(0)} \right), \quad (29)$$

with $\gamma > 0$. The anthropogenic emissions contributes to increase carbon concentration in the atmosphere (see Section 2.4), thus inducing climate change via the radiative forcing of GHGs. At the same time, global warming exerts two important feedbacks on the dynamics of carbon, affecting its exchanges with the biosphere (eq. 22) and the oceans (eq. 25).

2.3.3 The timeline of events in the climate box

In each period, we assume that events in the economy and the climate box happen sequentially with the surface temperature as the last variable to be determined:

1. total emissions produced in period t add to the current stock of atmospheric CO₂ concentrations, thereby modifying the biophysical equilibrium;
2. the increased carbon concentration affects oceans' marginal capacity to uptake CO₂;
3. carbon exchanges between the atmosphere and both biosphere and oceans take place, with the possible feedbacks from global warming;
4. the new equilibrium concentration of carbon in the atmosphere, $C_a(t)$, is determined;
5. $C_a(t)$ affects the new radiative forcing of GHG;

²⁵Radiative forcing is a measure of the influence a factor has in altering the balance of incoming and outgoing energy in the Earth-atmosphere system and it is an index of the importance of the factor as a potential climate change mechanism ([IPCC, 2007a](#)). To simplify, we use CO₂ as a proxy for all greenhouse gases and we consider only its radiative forcing.

6. the radiative forcing determines the entity of climate change, i.e. the increase in mean surface and upper oceans' temperature;
7. a set of stochastic shocks hitting the economy are drawn from a distribution whose density function is affected by the dynamics of surface temperature.

The last point provides the feedback between the climate evolution and the dynamics of the economy. We describe it in more details in the next Section.

2.4 Climate and economy co-evolution

The dynamics of climate and the economy are intimately intertwined, with multiple feedbacks affecting their evolution.

First, production of goods and energy entails CO₂ emissions in the atmosphere, thereby increasing its concentration. Total emissions (Em) are simply obtained by summing CO₂ emissions in the machine-tool industry (Em^{cap}), consumption-good sector (Em^{con}) and in energy production (Em^{en}):

$$Em(t) = \sum_{\tau} \left(\sum_i Em_{i,\tau}^{cap}(t) + \sum_j Em_{i,\tau}^{con}(t) + Em_{\tau}^{en}(t) \right), \quad (30)$$

where τ denote the vintage of machine or power plant. Emissions are obtained straightforwardly multiplying the coefficient of environmental friendliness of the machine (plant) at stake with the total amount of energy units (fuel units, in the case of the energy sector) used in period t .

At the same time, climate change impacts on the economic system via multiple, possibly catastrophic, events hitting labour productivity, firm energy efficiency, firm-level capital stocks and inventories, etc. (see section 4 for further details). Climate change originates from increasing radiative forcing due to higher and higher CO₂ concentration in the atmosphere. As it is well discussed in Pindyck (2013), the choice of how to represent global-warming induced damages is the most speculative element of the analysis, both because of the lack of robust empirical evidence and because of the neglect of societal adaptation processes.²⁶ At the same time it is the litmus test of the exercise.

Most IAMs simply assess the impact of climate-change on the economy via aggregate fractional GDP losses. The usual practice consists in specifying an ad-hoc functional form for the so-called *damage function* with arbitrary parameters.²⁷ The adoption of simple aggregate damage functions brings three further problems. First, by considering only GDP losses, IAMs do not distinguish between different types of possible damages. Second, the adoption of continuous and “smooth” damage functions rules out the treatment of catastrophic, more or less rare climate events. Finally, there is an absolute degree of certainty in the occurrence of the damage: whenever an increase in average surface temperature materializes, some output is deterministically destroyed.

In the attempt to overcome such problems, we employ a genuine bottom-up approach to climate impact modeling (Ciscar et al., 2011, 2012). More specifically, our stochastic *agent-based damage generating function* evolves over time according to the dynamics of the climate. At the end of each period, a draw from the distribution establishes the size of the shock affecting firms and workers. The impact of climate shocks are heterogeneous across agents (e.g. some firms can face disasters, while others mild events) and it can affect different variables (e.g. labor productivity, capital stock, etc.).

²⁶We notice that some advances in the empirical analysis of climate impacts are materializing (see Carleton and Hsiang, 2016) but, on the other side, we are not aware of attempts at accounting for these insights within standard IAMs.

²⁷For example, Nordhaus (2008) uses an inverse quadratic loss function, Weitzman (2009) proposes a negative exponential functional specification emphasizing the catastrophic role of large climate changes, while Tol (2002) uses sector and area specific loss functions.

The *disaster generating function* takes the form of a Beta distribution over the support $[0, 1]$, whose density satisfies:

$$f(s; a, b) = \frac{1}{B(a, b)} s^{a-1} (1-s)^{b-1}, \quad (31)$$

where $B(\cdot)$ is the Beta function and a, b are respectively the location and scale parameters. Both parameters are assumed to evolve across time reflecting changes in climate variables:

$$a(t) = a_0 [1 + \log T_m(t)] \quad (32)$$

$$b(t) = b_0 \frac{\sigma_{10y}(0)}{\sigma_{10y}(t)}, \quad (33)$$

where $\sigma_{10y}(t)$ captures the variability of surface temperatures across the previous decade and a_0, b_0 are positive integers.²⁸ Equations (32) and (33) shape the disaster generating function as a right-skewed, unimodal distribution, whose mass shifts rightward as temperature increases, thereby raising the likelihood of larger shocks.²⁹ Equation (33) determines the size of the right tail of the distribution and it allows one to account for the importance of climate variability on natural disasters (Katz and Brown, 1992; Renton et al., 2014), which has been increasingly recognized as a major driver of climate disasters (Thomalla et al., 2006; IPCC, 2012; Revesz et al., 2014), even if most of the models do not even mention it.³⁰

3 Macroeconomic and climate dynamics in the DSK model

The DSK model allows to jointly study the short- and long-run behavior of the economy under global warming and increasingly large and volatile climate shocks. The rising temperature associated with increasing emissions can lead to stronger and more volatile climate shocks, which in their turn can induce recessions and crises, possibly hampering also the growth performance of the economy even letting alone deeper welfare shocks (more in the conclusions). Hence, in presence of climate change, Solow's plea for macroeconomic models to jointly account for short- and long-run dynamics is even more relevant (see also Rogoff, 2016, on the importance of climate shocks for short-run dynamics). Thus, the ability of the DSK model to *simultaneously* account for short- and long-run features is, in our opinion, a key aspect of the overall exercise and also a major advantage over standard IAMs.

We will study the dynamics of the DSK model in the business-as-usual (BAU) benchmark scenario, where no climate policies are in place. The model is calibrated and initialized on the main features of the global economy in year 2000 and climate shocks are switched off.³¹ As it is typically the case in agent-based computational economics, the DSK model does not allow for analytical, closed-form solutions (for a discussion, Fagiolo and Roventini, 2012, 2017). We then perform extensive Monte Carlo simulation exercises to study the properties of the stochastic processes governing the co-evolution of micro- and macroeconomic variables. More specifically,

²⁸For modelling purposes we estimate the standard deviation of the previous ten recorded temperatures; however, a widely used measure of climate variability corresponds to the count of extreme temperatures (IPCC, 2012).

²⁹Naturally, any distribution would be feasible for sampling climate shocks. Our choice should be considered as a first attempt towards a micro-foundation of climate damages. The Beta distribution is flexible enough to explore a wide range of scenarios and to genuinely account for fat-tailed climate risks (Ackerman et al., 2010; Weitzman, 2011; Pindyck, 2012).

³⁰The majority of studies accounting for climate catastrophes employ some variant of the DICE model (see also Gerst et al., 2010; Berger et al., 2016) where an arbitrary large output loss is identified as a catastrophe. To the contrary, our modeling effort should be seen as an attempt at providing evidence of how large shocks at the individual level might impact on aggregate dynamics, outside optimal growth paths.

³¹In particular, the model has been calibrated through an indirect calibration exercise (Windrum et al., 2007).

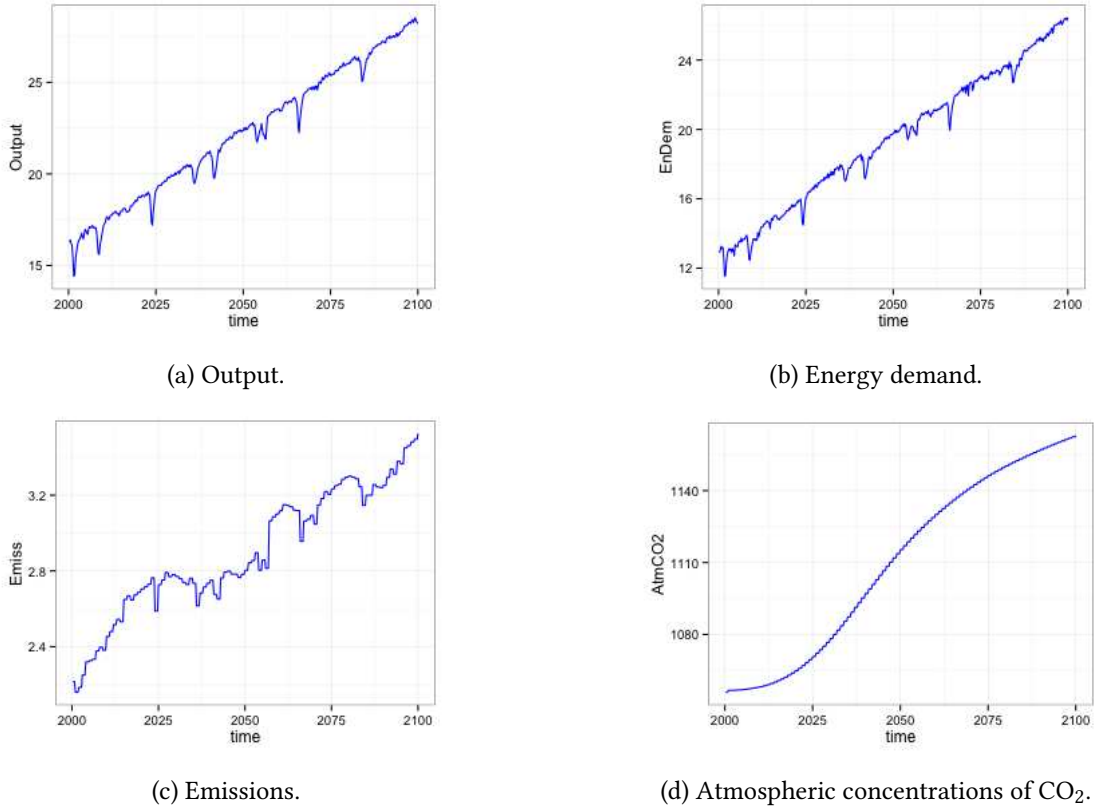


Figure 2: Long-run evolution of selected variables, log-scale for panels 2a, 2b and 2c.

we run the model for 400 periods, which are to be interpreted as quarters, thereby obtaining projections until year 2100. As the model generates multiple possible trajectories, each linked to a different pattern of technical change in the industrial and energy sectors, we rely on Monte Carlo experiments of size 100. Note that emergent non-ergodicity, tipping points, irreversibility and hysteretic phenomena typically characterize the dynamic of the DSK model (more on that in Brock, 1988; Brock and Xepapadeas, 2003; Dosi et al., 2017b).³²

We will first discuss in Section 3.1 the macroeconomic and climate variable projections obtained by simulating the DSK model. We will then show the economic and climate stylized facts that the model is able to replicate (cf. Section 3.2).

3.1 Macroeconomic and climate variable projections

Simulation results show that the DSK model is able to track the empirical evolution of the economy with respect to a variety of measures, including output growth rates, unemployment levels, emissions growth rates and energy consumption. Figure 2 shows a representative run for some quantities of interest, while MC averages and standard deviations for the main macroeconomic and climate variables are collected in Table 1.

We robustly find endogenous growth of output and energy demand, which increase at relatively similar rates. Emissions steadily grow as well, but at a lower pace, in line with recent evidence (cf. Olivier et al., 2015). Moreover, projections indicate that the economic system grows with endogenous fluctuations punctuated by major crises,³³ which in turn leads to the emergence of persistent unemployment. Finally, the share of re-

³²Extensive tests show that the results are robust to changes in the initial conditions for the microeconomic variables of the model. In addition, they show that, for the statistics under study, Monte Carlo distributions are sufficiently symmetric and unimodal. This justifies the use of across-run averages as meaningful synthetic indicators. All our results do not significantly change if the Monte Carlo sample size is increased. Details available from the authors.

³³See e.g. NBER (2010); Claessens and Kose (2013). In our framework, a crisis is defined as an event where the yearly loss of output is higher than a 5% threshold.

Table 1: Summary statistics on selected variables under business-as-usual scenario and no climate shocks.

	MC average	MC st. dev.		MC average	MC st. dev.
GDP growth	0.032	0.005	Share of emissions from energy sector	0.614	0.201
Likelihood of crises	0.121	0.076	Share of green energy	0.299	0.285
Unemployment	0.120	0.032	Periods green energy above 20%	0.330	0.103
Energy demand growth	0.031	0.002	Emissions growth	0.031	0.003
GDP volatility	0.278	0.024	Consumption volatility	0.187	0.021
Investment volatility	0.313	0.022	Volatility of firm total debt	0.638	0.069
Volatility of energy demand	0.212	0.040	Emissions volatility	0.327	0.025
Emissions at 2100	26.90	9.236	Temperature at 2100	4.54	0.509

Note: All values refer to a Monte Carlo of size 100. Emissions are expressed in GtC, which can be converted in GtCO₂ using the following conversion factor: 1 GtC = 3.67 GtCO₂. Temperature is expressed in Celsius degrees above the preindustrial level, which is assumed to be 14 Celsius degrees.

renewable energies in total energy production exhibits an average of 30% over the whole time span (which we take to stand for the period 2000-2010). Renewable energies account for more than 20% only in one third of the periods, thus indicating that transitions towards a green economy in a *business-as-usual* scenario are quite unlikely.

The DSK model delivers also reasonable results in terms of projected global mean surface temperature. Figure 3 shows the dynamics of temperature along the whole time span for a Monte Carlo of size 50 and reports their distribution at the middle (2050) and final point (2100) of the simulation. Our results are relatively in line with those from the most widely used IAMs (see Clarke et al., 2009; Gillingham et al., 2015). Note, however, that the mean and median values of our projections are somewhat higher than those of other models (details are provided in Appendix B). This outcome is driven by the presence, within the carbon cycle (see Section 2.3), of different feedback loops yielding non-linear dynamics.³⁴ In particular, we robustly find a precise behavior in the projection of temperature: a first phase of gradual increase is followed by a period (indicatively located between 2025 and 2050) where climate change accelerates dramatically, and a third phase, where climate change lowers its pace and displays an almost constant growth. The path-dependency showed by such projections calls for policy interventions that occur early enough to avoid an increase in temperatures which is substantially above the two percent threshold. Finally, Figure 3b shows the Monte Carlo distribution of temperature at the middle (2050) and final (2100) point of the simulation. As in the BAU benchmark scenario, climate shocks are switched off, such distributions characterize the uncertainty surrounding temperature projections stemming only from technical change (Dosi, 1988). The mean, support, and tails of the temperature distribution all increase over time, again suggesting the non-linear and accelerating dynamics of climate change.

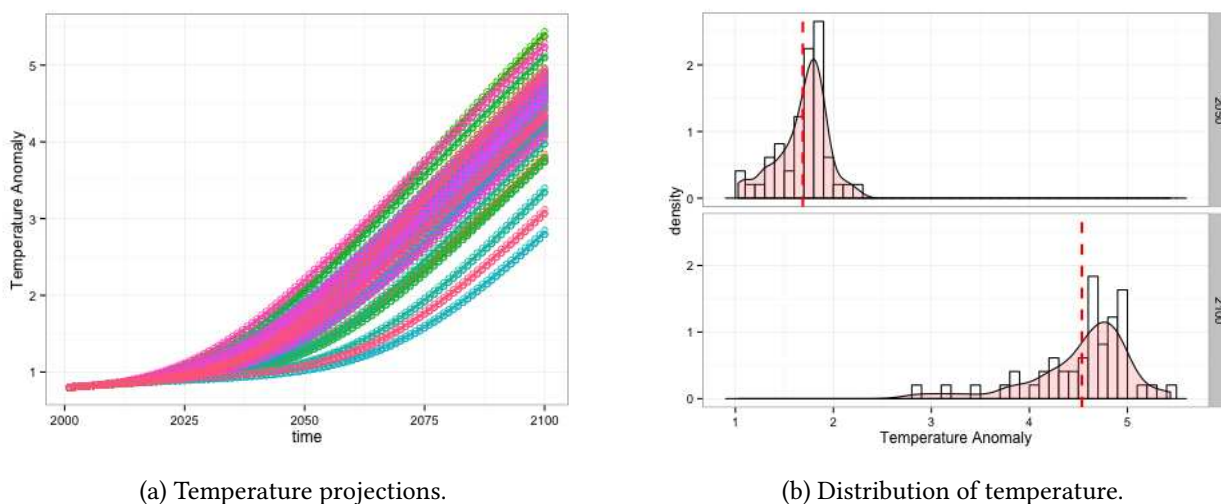
3.2 Replication of empirical regularities

Beyond these general features, the DSK model is able to jointly reproduce a large ensemble of micro and macro stylized facts characterizing short- and long-run behavior of economies. Table 2 reports the main empirical regularities replicated by the model together with the corresponding empirical studies. We discuss here the most relevant empirical regularities, leaving additional details to appendix A.

Let us begin with business cycle stylized facts.³⁵ Once we remove the trend with a bandpass filter (Baxter and King, 1999), output, investment and consumption series display the familiar “roller-coaster” dynamics (see e.g. Stock and Watson, 1999; Napoletano et al., 2006, and Appendix B for plots of the filtered series). In line with the empirical evidence, consumption is less volatile than GDP, while the fluctuation of investment are

³⁴These feedbacks have been calibrated according to Serman et al. (2013) and C-ROADS model documentation. See <https://www.climateinteractive.org/tools/c-roads/technical>.

³⁵On the relevance of accounting for business cycles features for a climate-oriented macroeconomic model see Rogoff (2016).



(a) Temperature projections.

(b) Distribution of temperature.

Figure 3: Temperature projections and their density estimates. Both graphs refers to a Monte Carlo of size 50. Red dashed lines in panel 3b indicate mean values.

wilder. Moreover, firms' total debt, which is an imperfect proxy for the financial side of the model, shows significantly ampler fluctuations than output (see table 1). Finally, the real, financial and energy parts of the economic system appear to be strongly correlated across down-swings and, to a lower extent, upswings (see appendix B for details). This finding corroborates some recent evidence (Albuquerque et al., 2015) showing that correlations between economic fundamentals and financial markets are particularly strong across "episodes".

The co-movements between macroeconomic variables at the business cycle frequencies are well in tuned with the literature (see figure 7c in Appendix B; cf. Stock and Watson, 1999; Napoletano et al., 2006). Cross-correlations between GDP and the other main macroeconomic variables (see figure 4 and Appendix A) reveal that consumption and investments are pro-cyclical and coincident. Unemployment and prices are counter-cyclical and inflation is slightly pro-cyclical. Finally, energy demand shows a lagging and pro-cyclical pattern akin to the one of firm-level debt (see Claessens et al., 2009 on the credit cycle). This is in line with the evidence that industrial production causes energy use at business-cycle frequencies (Thoma, 2004).

Beyond business-cycle properties, the DSK model reproduces fairly well the long-run positive co-integrating relationships between energy and output (for a survey see Ozturk, 2010) and GDP and emissions (Triacca, 2001; Attanasio et al., 2012). Figure 2 shows that energy demand, output and emissions co-evolve in the baseline scenario (see also Figure 7c in Appendix B for details). Such patterns are confirmed by a series of co-integration tests (cf. Table 3), which show a statistically significant connections between output growth, energy demand, and emissions.

Finally, we have checked the consistency of the DSK model's emission and temperature projections with those produced by other IAMs. This step is crucial to meaningfully compare the effects of micro climate damages on macroeconomic performances with those obtained by other models. Results are in line with the literature and further details are included in Appendix B.

4 Climate damages

Climate damages are usually perceived as the most speculative element of the overall integrated assessment modelling effort (Pindyck, 2013) and often rely on *ad-hoc* damage functions (Tol, 2002). Even though the effects of climate change are hardly understandable without extensive data and reasonable variance in temperatures, we try to provide a genuine micro-foundation of aggregate climate damages exploiting the potentiality of

Table 2: Main empirical stylized facts replicated by the DSK model.

Stylized facts	Empirical studies (among others)
Macroeconomic stylized facts	
SF1 Endogenous self-sustained growth with persistent fluctuations	Burns and Mitchell (1946); Kuznets and Murphy (1966) 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 Synchronization 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)

Figure 4: Cross-correlations between output and main macroeconomic aggregates. Bandpass-filtered (6,32,12) series. Average cross-correlations from a Monte Carlo of size 100. Cons: consumption; Inv: investment; Tot-Debt: Firm total debt; EnDem: energy demand; Infl: inflation; Unempl: unemployment.

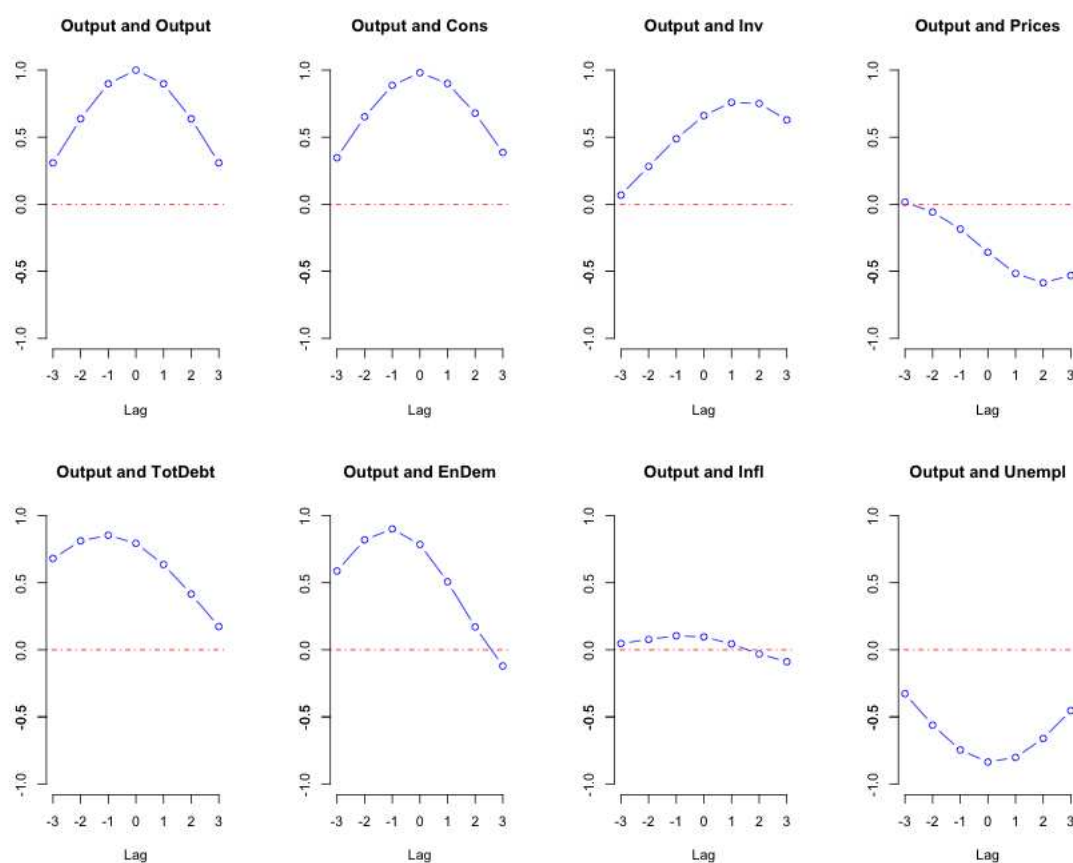


Table 3: Cointegration tests for output, energy demand and emissions. All values refer to a Monte Carlo of size 100. In the Engle-Granger procedure critical values for significance levels are taken from [Banerjee et al. \(1993\)](#) and there is evidence of cointegration if the test statistic is lower than the threshold. In the Phillips-Ouliaris procedure we used the so-called P_z test; evidence of cointegration if test statistic larger than the threshold. In the Johansen procedure both constant and trends are assumed, while seasonality is not considered, the lag order is set to 2 and critical values are taken from [Osterwald-Lenum \(1992\)](#). There is evidence of two cointegrating vectors if the $r=0$ and $r<=1$ hypothesis are rejected while the $r<=2$ is not; if the latter is rejected as well, all vectors are co-integrated.

	Test statistic	5%-threshold	MC st. dev.	Runs passing test
Engle-Granger Procedure				
Output-EnDem	-6.738	-2.58	2.456	96%
Emissions-Output	-3.861	-2.58	2.969	64%
Emissions-EnDem	-7.004	-2.58	3.401	92%
Phillips-Ouliaris Procedure				
Output-EnDem	272.196	55.19	115.231	100%
Emissions-Output	136.393	55.19	131.115	100%
Emissions-EnDem	258.777	55.19	132.856	100%
Johansen Procedure (three-variate VAR)				
$r<=2$	9.245	12.25	4.116	59% (null rejected)
$r<=1$	40.146	25.32	13.007	91% (null rejected)
$r=0$	97.849	42.44	17.581	100% (null rejected)

Table 4: First and second moment of climate shock size over time. Reported values are averages over a Monte Carlo of size 100.

	2000	2025	2050	2075	2100
Average value of shocks	1.044%	1.099%	1.905%	5.357%	4.788%
Standard deviation of shocks	1.006%	1.053%	1.768%	4.583%	4.034%
Coefficient of variation	0.963	0.958	0.929	0.868	0.844

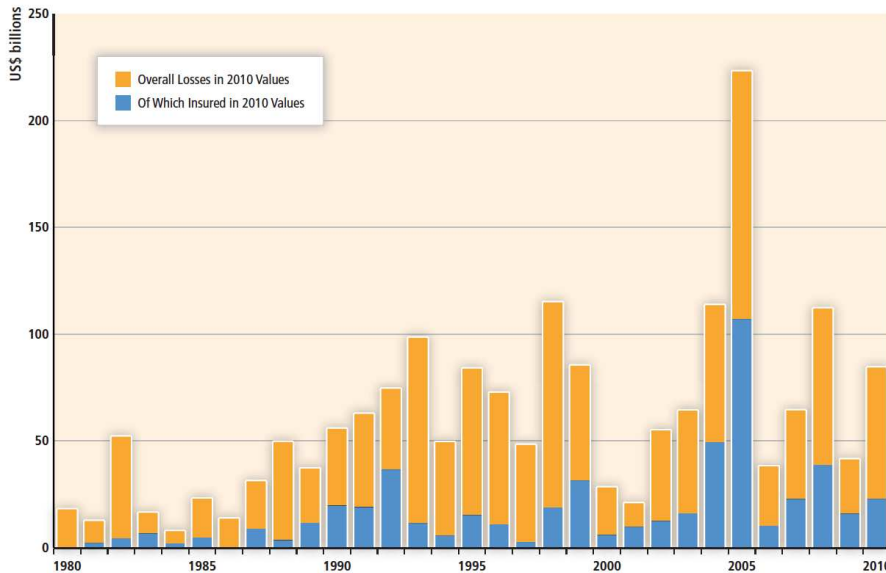


Figure 5: Climate Damages and Shocks. The figure presents monetary estimates (in 2010 USD) of climate and weather related damages. The overall losses do not include those associated to geophysical events. Source: IPCC (2013).

agent-based models (Balint et al., 2017; Lamperti et al., 2016).

We now allow for feedbacks from climate to the economy in the DSK model, switching on climate shocks, whose likelihood and magnitude depend on the dynamics of temperature anomaly (cf. Section 2.4). The average size of climate shocks lies between 1% (at the beginning of the simulation) and 5.4% (during the last quarter of the simulation), and they are fairly consistent with those used in other IAMs (e.g. Nordhaus and Sztorc, 2013). However, contrary to standard IAMs, the damage generation in the DSK model accounts for both increasing size and inter-annual variability of damages (cf. Table 4), as documented by IPCC (2013) for the period 1980-2010 (see Figure 5).

We analyze eight scenarios characterized by different targets for climate damages (see Dell et al., 2014, for a survey of the empirical literature addressing micro impacts of temperature and weather changes), which heterogeneously impact on firms and workers. In particular, we consider the following four climate shock regimes and their possible combinations:

- *Labour productivity (LP) shocks.* Labor productivity ($A_{i,\tau}^L$ and $B_{i,\tau}^L$) falls by a factor that varies across firms, as climate change negatively impacts on workers' operative and cognitive tasks (Seppanen et al., 2003, 2006).
- *Energy efficiency (EF) shocks.* Firm-level energy efficiency ($A_{i,\tau}^{EE}$ and $B_{i,\tau}^{EE}$) is reduced as climate shocks increase energy requirements in production activities (e.g. more stringent needs of cooling in response to higher temperatures or partially ruined machines in response to natural disasters).
- *Capital stock (CS) shocks.* Climate shocks destroy firm-level endowments of physical capital. Consumption-good firms lose part of their stock of machines, while capital-good firms lose part of the machines they are producing.
- *Inventories (INV) shocks.* Firms' consumption good inventories are reduced due to the effects of climate and weather events, such as typhoons and tornado.

While the first two scenarios account for the gradual effects of climate change, which modifies working conditions, the latter ones refer to direct damages stemming from the realization of possibly extreme climate or

Table 5: Main economic performances under heterogeneous climate damages and shock scenarios. Monte Carlo standard deviations in parentheses.

<i>Shock scenario</i>	<i>Output growth rate</i>	<i>Likelihood of crises</i>	<i>Unemployment</i>
No shocks	3.21% (0.005)	12.1% (0.076)	12.0% (0.032)
Labour productivity (LP)	1.27% (0.006)	21.6% (0.051)	22.2% (0.041)
Energy efficiency (EF)	3.05% (0.004)	17.5% (0.033)	13.2% (0.033)
Capital stock (CS)	2.91% (0.004)	23.4% (0.052)	13.8% (0.035)
Inventories (INV)	3.16% (0.004)	18.6% (0.048)	13.1% (0.046)
LP&EF	1.03% (0.003)	25.9% (0.074)	22.6% (0.047)
LP&CS	0.82% (0.006)	26.0% (0.044)	21.0% (0.050)
CS&EF	2.65% (0.004)	20.1% (0.039)	14.6% (0.038)
CS&INV	2.88% (0.003)	21.1% (0.053)	14.0% (0.047)

Note: All values refer to a Monte Carlo of size 100.

weather related events (e.g. [IPCC, 2013](#)). Even if the ultimate effect of all these scenarios is a loss of GDP, different channels are at stake and tipping points and non-linear effects can possibly arise.³⁶

The results of our computational experiments are summarized in Table 5, where we report the average values of output growth, unemployment and likelihood of crises together with their Monte Carlo standard deviations for each explored scenario. Simulation results show that climate shocks targeting different variables (labor productivity, energy efficiency, capital stock, inventories) have a different impact on economic dynamics, with labour productivity and capital stock shocks producing the largest harm to the economic system (cf. Table 5).³⁷ For instance, GDP growth under labor productivity shocks is almost one third of the one obtained in absence of climate damages (1.27% vs. 3.21%), with employment and the likelihood of crises rising by a factor close to 1.8 (see Table 5). On the other hand, when shocks hit firms’ inventories, the economy exhibits a pace of growth similar to the benchmark scenario, climate damages exacerbate economic instability and the emergence of crises.

Such a heterogenous impact of climate shocks stems from the different channels through which climate change harms the economy. Labour productivity shocks sabotage the firms’ “Schumpeterian engine”, thus increasing production costs more than in presence of energy efficiency shocks (in line with the empirical evidence [EU, 2014](#)). This, in its turn, leads to a harsher contraction in GDP growth and to a surge in unemployment. In a different manner, climate shocks to the capital stock magnify the instability of the economy – mainly via the private debt channel and lower firms’ productive capacity – while keeping a relatively moderate unemployment level, as the loss of the most efficient machines increase labour demand.

³⁶The empirical literature has confirmed that both warming and climate events exert a non-negligible impact. For example, high temperatures are found to reduce output at plant level by 2% in the automobile sector, while extreme windstorms produce a 26% decline of daily output ([Cachon et al., 2012](#)).

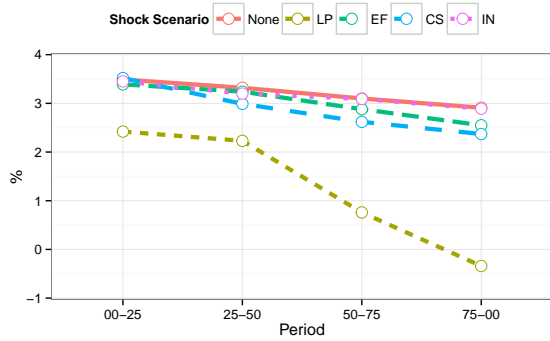
³⁷Further scenarios, obtained by means of further combinations of shock targets, are not reported for the sake of brevity and are available from the authors upon request.

Table 6: Heterogeneous climate shocks vs. standard damage function. Up to the last column normalized economic performances relative to those obtained with Nordhaus and Sztorc (2013) damage function targeting output are reported. Absolute value of simulation t-statistic of H_0 : “no difference between baseline (Nordhaus and Sztorc, 2013) and the experiment” in parentheses. In the last column, instead, we report performances relative to the “no shocks” scenario.

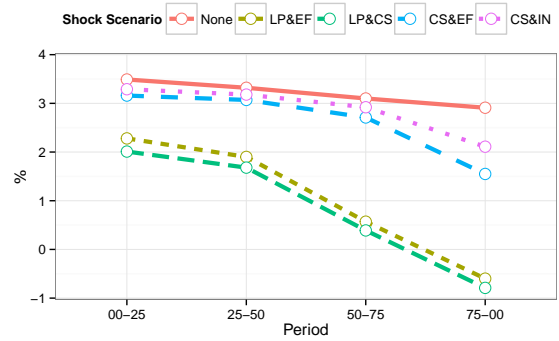
<i>Shock Scenario</i>	<i>Output growth rate</i>	<i>Likelihood of crises</i>	<i>Unemployment</i>	$\frac{GDP_{2100}}{GDP_{2100}(\text{“no shocks”})}$
Standard IAM	1.000 (0.00)	1.000 (0.00)	1.000 (0.00)	0.944* (1.90)
Labour productivity (LP)	0.428** (24.07)	1.854** (10.96)	1.872** (19.61)	0.151** (38.12)
Energy efficiency (EF)	0.947 (1.56)	1.445** (6.97)	1.126** (2.61)	0.865** (8.07)
Capital stock (CS)	0.917** (3.74)	1.986** (12.96)	1.167** (3.79)	0.744** (12.34)
Inventories (INV)	1.001 (-0.56)	1.478** (7.64)	1.092* (1.96)	0.989 (0.45)
LP&EF	0.327** (36.35)	2.152** (13.54)	1.836** (18.64)	0.119** (39.81)
LP&CS	0.303** (29.84)	2.211** (16.81)	1.748** (15.16)	0.104** (44.27)
CS&EF	0.853** (7.80)	1.580** (9.98)	1.222** (5.23)	0.596** (22.76)
CS&INV	0.910** (4.63)	1.748** (10.39)	1.179** (3.51)	0.731** (8.45)

Note: All values refer to a Monte Carlo of size 100. ** Significant at 5% level; * Significant at 10% level.

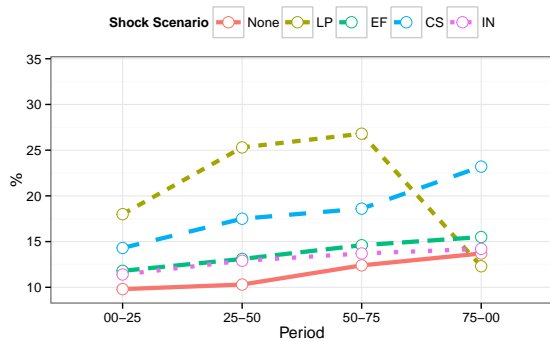
Figure 6: Economic performances under climate shocks by time slices. LP: Labour Productivity shocks ; EN: Energy Efficiency shocks; CS: Capital Stock shocks; IN: Inventories shocks.



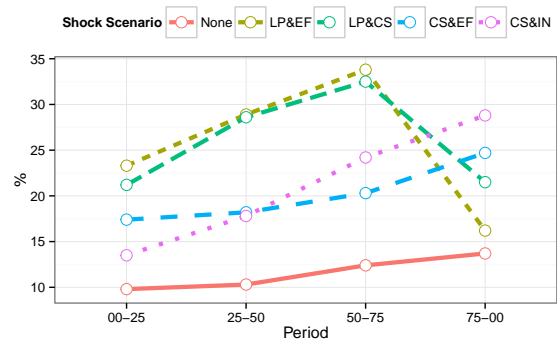
(a) Output growth; shocks un-combined.



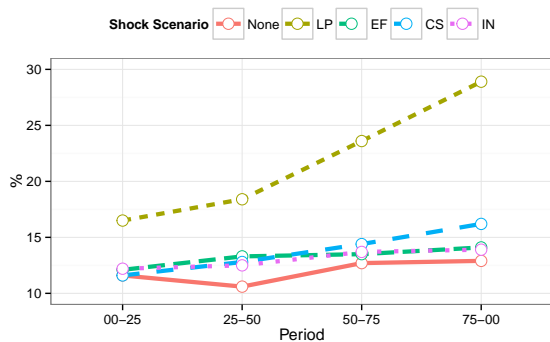
(b) Output growth; shocks combined.



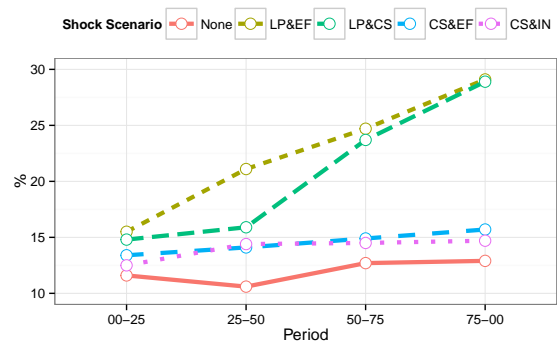
(c) Likelihood of crises; shocks un-combined.



(d) Likelihood of crises; shocks combined.



(e) Unemployment; shocks un-combined.



(f) Unemployment; shocks combined.

Note: All panels refer to a Monte Carlo of size 100. Average values are reported. Monte Carlo standard deviations for each case are available from the authors.

The heterogeneous impact of shocks is also linked by the highly *non-linear* dynamics of the economy. We report in Figure 6 the average MC value of output growth rate, likelihood of crises and unemployment in the different scenarios, segmenting the simulation into 4 non-overlapping windows lasting 25 years each. While in most of scenarios, growth and economic stability are almost unaffected in the first time period, the impact of shocks magnify and diverge over time. In line with our previous results, capital stock (CS) and labour productivity (LP) shocks have a different impact on the dynamics of the economy. In the *LP* scenario, growth performance is progressively harmed until the economy reaches a stagnation plateau, with low volatility and rising unemployment. On the contrary, in presence of CS damages, rising temperatures have a milder impact on output growth, but the economy becomes more and more unstable over time. These results are reinforced when inventories shocks are also present. Finally, energy efficiency shocks are less harmful than other scenarios, but by increasing energy demand, they amplify the direct impact of *IN*, *CS* and *LP* damages.

Let us now compare the economic damages from climate change observed in the DSK model with those generated by standard IAMs. More specifically, in Table 6, we test for the existence of a statistically significant difference with respect to the results we would have obtained employing a standard damage function targeting output adopted in Nordhaus and Sztorc (2013), which is the latest available version of the most widely used IAM.³⁸ We find that climate shocks have a much more catastrophic impact on the economy in our model than in CGE-based IAMs (see Table 6). And this holds notwithstanding the average size of climate shocks is comparable (see Nordhaus, 2014). In particular, in all eight scenarios, at least two third of the economic indicators are significantly worse than the ones obtained employing the aggregate quadratic damage function à la Nordhaus and Sztorc (2013). In some cases, when shocks are combined, the difference is dramatic (see, in particular, *LP&EF* and *LP&CS* scenarios in Table 6). The more catastrophic impact of climate change in the DSK model vis-à-vis CGE-based IAMs is due to the presence of non-linearities and the endogenous emergence of *tipping points* provoked by heterogenous micro-shocks percolating via different channels (see Figure 6).

Such differences are even more vivid when one considers output levels at the end of the century, as commonly done in the integrated assessment literature (cf. last column of Table 6). The ratio of GDP levels in 2100 between the “no shocks” and the Nordhaus-Sztorc damage function case is 94%. However, the ratio falls to 74% when climate shocks hit the capital stock and even to 15% when climate change harms labor productivity. When LP and CS climate shocks are coupled, the economic performance collapses: GDP average growth falls below the 1% average over the century, unemployment doubles, and the likelihood of crises reaches 25%. Note also that the results robustly confirm the wide heterogeneity observed in the different climate-shock scenarios

5 Discussion and concluding remarks

In this paper, we have presented the first *agent-based integrated assessment model*, which explore the co-evolution between economic dynamics and climate change. The Dystopian Schumpeter meeting Keynes (DSK) model builds upon Dosi et al. (2010, 2013, 2016) and it allows for non-linear climate dynamics as in Sterman et al. (2013). Economic activity is linked to the emissions of greenhouse gasses, which increase temperature and lead to climate change. Higher temperatures trigger micro climate shocks, which, by differently impacting on workers’ labor productivity and on firms’ energy efficiency, capital stock and inventories, affect the macroeconomic performance via possible catastrophic events.

Simulation results show that the DSK model is able to match a wide ensemble of micro and macro stylized facts concerning climate change and economic dynamics. Moreover, simulation experiments show a substantial lack of isomorphism between the effects of micro and macro level shocks, as it is typical in complex system

³⁸The damage function in Nordhaus and Sztorc (2013) takes the following form: $L(x) = 1/(0.00267x^2)$.

models (see [Flake, 1988](#); [Tesfatsion and Judd, 2006](#)). The effects of micro climate shocks are indeed amplified by the interactions of heterogeneous agents along an evolving network structure of investment relationships across firms, and by the deep uncertainty resulting from technical and climate change dynamics. System stability is particularly harmed by climate shocks affecting capital stocks and inventories, while stagnating growth and soaring unemployment result from shocks to the labour productivity of workers.

Our results also show that climate damages from uncontrolled emissions are substantial and much more severe than predicted by standard integrated-assessment models (IAMs, see e.g. [Nordhaus, 1992, 2014](#)), possibly leading to the emergence of *tipping points* and irreversible outcomes. In the next future, we are planning to extend our impact analysis to include health and mortality. However, even at the current stage our results thus provide a clear support to the hypothesis that the current estimates of economic losses produced by climate shocks are biased downwards (see also [Hallegatte et al., 2007](#); [Stern, 2016](#)) and that, in view of the increasing magnitude and variance in impacts, timing for climate policy is crucial (see also [Lamperti et al., 2015](#)).

In such a framework, policy interventions become more complex than in standard IAMs, which simply study monetary incentives (subsidies) and carbon taxes. The DSK model can provide a flexible laboratory for more ambitious policy experiments, to study the joint impact of different climate, energy, innovation, fiscal and monetary interventions on economic and climate change dynamics. This is the most urgent point in our future research agenda. Further, we plan to use the model to explore the issue of policy urgency, paying particular attention at the path-dependent nature of different economic and climate processes. Finally, as for model development, we will exploit the structural heterogeneity brought about by agent based modelling to analyse the climate-inequality nexus and the links between energy industry and the financial system.

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A Appendix - Model details and model closure

In this appendix we present the full formal structure of the real side of the model discussed in section 2. We start with the equations describing the search processes and the determination of production and prices in the capital-good sector. Next, we turn to the equations related to the determination of production, investment, prices and profits in the consumption-good sector.

A.1 The capital good industry, complements.

Capital-good firms' technology is defined by a set of six firm-specific coefficients composed by $A_{i,\tau}^k$ with $k = \{L, EE, EF\}$, which represent the technical features of the machine produced, and $B_{i,\tau}^k$, 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 (3), (5) and (6) in section 2. 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 (7). 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, $NC_i(t)$)³⁹ consumption-good firms thus have access to imperfect information about the available machines.

A.2 The consumption good industry, complements.

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 $D_j^e = f[D_j(t-1), D_j(t-2), \dots, D_j(t-h)]$, desired inventories (N_j^d), and the actual stock of inventories (N_j):

$$Q_j(t)^d = D_j^e(t) + N_j^d(t) - N_j(t), \quad (34)$$

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).⁴⁰

$$EI_j^d(t) = K_j^d(t) - K_j(t). \quad (35)$$

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 (7). 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 (9). 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 $l_j(t)$:

$$E_j(t) = -\omega_1 p_j(t) - \omega_2 l_j(t), \quad (36)$$

where $\omega_{1,2} \geq 0$.⁴¹ 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

³⁹The random sample of new customers is proportional to the size of $HC_i(t)$. In particular, $NC_i(t) = YHC_i(t)$, with $0 \leq Y \leq 1$.

⁴⁰In 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.

⁴¹Such unfilled demand is due to the difference between expected and actual demand. Firms set their production according to the

finally linked to their competitiveness through a “quasi” replicator dynamics:

$$f_j(t) = f_{j,t-1} \left(1 + \chi \frac{E_j(t) - \bar{E}_t}{\bar{E}_t} \right), \quad (37)$$

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

A.3 The banking industry, complements.

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

$$c_j(t)Q_j(t) + EI_j(t)^d + RI_j(t)^d \leq NW_j(t)^d + Deb_j(t)^d \quad (38)$$

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 an unmodeled Central Bank to grant credit above the funds obtained through deposits from firms according to a multiplier $k > 0$:

$$MTC_t = k \sum_{j=1}^N NW_{j,t-1}. \quad (39)$$

Total credit 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:

$$\sum_{j=1}^N Deb_j(t) = Loan(t) \leq MTC_t. \quad (40)$$

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

A.4 Consumption, taxes and public expenditures

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. 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):

$$\sum_{i=1} Q_i(t) + \sum_j Q_j(t) = Y_t \equiv C_t + I_t + \Delta N. \quad (41)$$

B Appendix - Model validation and model dynamics

In line with the indirect inference approach discussed in [Windrum et al. \(2007\)](#) and [Fagiolo et al. \(2007\)](#) and following the prevailing practice in the agent based modelling literature (see, among others, [Dosi et al., 2010, 2013](#); [Riccetti et al., 2013](#); [Lengnick, 2013](#); [Dosi et al., 2015](#); [Assenza et al., 2015](#); [Safarzyńska and van den Bergh, 2016](#)), the DSK model is validated

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.

through the replication of empirical stylized facts, both concerning micro and macro aspects of the economic system.⁴² Table 2 in the main text reports the empirical regularities that the model replicates. Due to space availability, we invite the interested reader to contact the authors in order to obtain additional information on the estimation of parametric or non-parametric distributions that are requested to examine the presence of some empirical regularities (e.g. fat-tails). For what concerns other properties, this appendix provides evidences that complement the main text. In addition, we refer to Dosi et al. (2016) for an extensive illustration of the stylized facts reproduced by a previous version of the DSK model.

Figure 7 shows different panels reporting the behaviour of main macroeconomic aggregates at business cycle frequency and their correlation structure. The relationships among main macroeconomic aggregates is well tuned with the literature (see figure 7c). Output, aggregate consumption, investments, firms' debt and demand of energy are positively and strongly correlated, while prices negatively associate with investments. Unemployment decreases when economy expands and its correlation with inflation is extremely close to zero. Beyond these general tendencies, table 7 provides evidence on leading and lagging indicators, which appear fairly similar to those proposed in Stock and Watson (1999) and Napoletano et al. (2006).

Table 7: Auto-cross correlations between output and main macroeconomic aggregates. Bandpass-filtered (6,32,12) series. Average auto-cross correlations from a Monte Carlo of size 100. Monte Carlo standard deviations are reported below each coefficient.

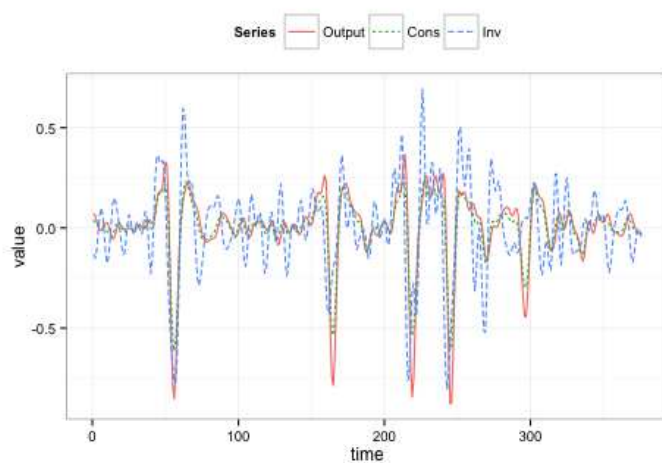
	Lag of Output						
	-3	-2	-1	0	1	2	3
Output	0.311	0.642	0.902	1.000	0.902	0.642	0.311
	0.040	0.031	0.010	0.00	0.010	0.031	0.040
Cons	0.354	0.652	0.890	0.981	0.901	0.684	0.392
	0.051	0.031	0.022	0.004	0.011	0.020	0.033
Inv	0.073	0.282	0.491	0.664	0.761	0.752	0.631
	0.111	0.104	0.084	0.061	0.060	0.060	0.060
Prices	0.023	-0.063	-0.184	-0.362	-0.522	-0.591	-0.534
	0.141	0.140	0.110	0.081	0.064	0.062	0.071
TotDebt	0.684	0.811	0.852	0.794	0.640	0.412	0.172
	0.044	0.032	0.021	0.023	0.032	0.041	0.040
EnDem	0.590	0.821	0.902	0.791	0.514	0.170	-0.124
	0.041	0.040	0.040	0.041	0.051	0.053	0.054
Infl	0.054	0.081	0.104	0.103	0.042	-0.031	-0.092
	0.021	0.030	0.031	0.034	0.021	0.022	0.023
Unemployment	-0.330	-0.562	-0.754	-0.843	-0.801	-0.663	-0.453
	0.041	0.041	0.032	0.031	0.030	0.021	0.032

Here we also check whether the emissions pathways generated by the model deliver reasonable results in terms of projected global mean surface temperature. Figure 3 in the main text shows the dynamics of temperature along the whole time span for each of the runs used in a typical Monte Carlo ensemble and report their distribution at the middle and final point of the simulation. Our results find relatively in line with those from most widely used IAMs (8b), even though mean and median values of our projections (reported also in table 1) are slightly higher than counterparts from other models (see also Clarke et al., 2009; Gillingham et al., 2015). A possible reason for this effect is given by the presence, within the carbon cycle (see section 2.3), of different feedbacks loops giving rise to non-linear dynamics.⁴³

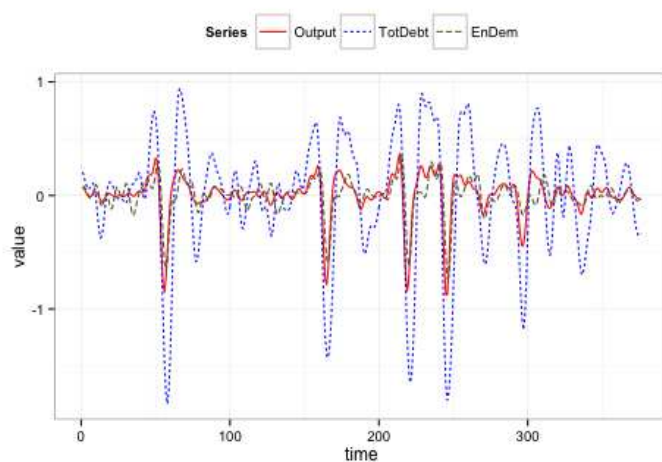
⁴²Notice that alternative approaches for large scale models are under development. See Barde (2016); Lamperti (2017, 2016); Lamperti et al. (2017); Guerini and Moneta (2016).

⁴³These feedbacks have been calibrated according to Sterman et al. (2013) and C-ROADS model documentation. See <https://www.climateinteractive.org/tools/c-roads/technical>.

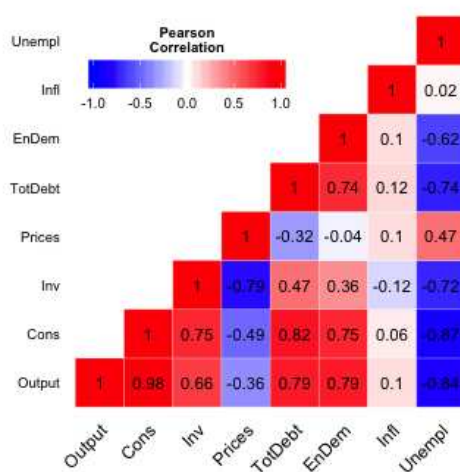
Figure 7: Filtered series and their correlation structure. Panel 7a and Panel 7b presents the behaviour of selected Bandpass-filtered (6,32,12) series for a randomly chosen Monte Carlo run. Panel 7c presents the correlation structure emerging from filtered series and refers to a Monte Carlo of size 100.



(a) Output, Consumption and Investments.

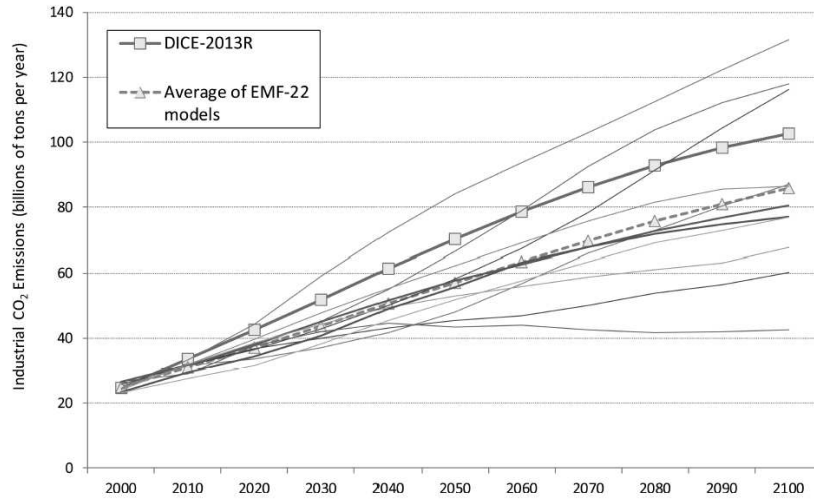


(b) Output, Total private debt, Energy demand.



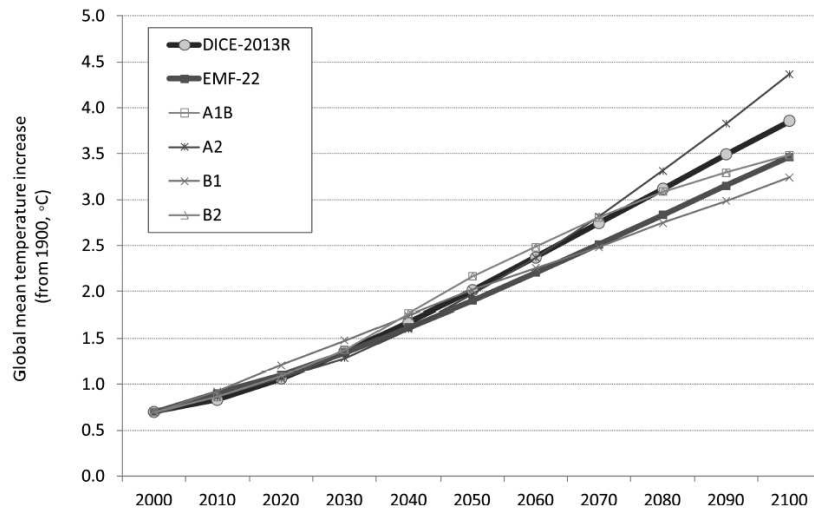
(c) Correlation structure.

Figure 8: Industrial emissions and temperature projections from different models. Source: Nordhaus (2014)



(a) Industrial emissions.

Note: Projected industrial CO₂ emissions in baseline scenario. The heavy dashed line with triangles is the average of the 11 models surveyed in the EMF-22 project. The heavy line with squares is the DICE-2013R version. The light lines are the individual EMF-22 models. The EMF results are described in Clarke et al. (2009) Emissions are expressed in GtCO₂, which can be converted in GtC using the following conversion factor: 1 GtC = 3.67 GtCO₂.



(b) Temperature anomaly.

Note: Global mean temperature increase as projected by IPCC scenarios and integrated assessment economic models. The figure compares the projections of four scenarios using IPCC scenarios with those of the DICE-2013R model and the average of 10 EMF-22 integrated economic models. The letters A1B, A2, B1, and B2 represent the results of four IPCC standardized emissions and the ensemble of climate model projections from the IPCC Fourth Assessment Report. The runs shown in panel 8b take the industrial CO₂ concentrations from the EMF-22 models. These are then combined with estimates of land-use CO₂ emissions and the radiative forcings for other GHGs from the RICE-2010 model and finally put into the climate module of the RICE-2010 model. The 10 models were ETSAPTAM, FUND, GTEM, MERGE Optimistic, MERGE Pessimistic, MESSAGE, MiniCAMBASE, POLES, SGM, and WITCH.

C Appendix - Model parameters

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	100
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 $\Delta \bar{A}B$ 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
R&D share investment in green tech.	$\eta_g e$	0.4
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/m ²	Sterman et al. (2013)
GtC to GtCO ₂ conversion factor		3.67		IPCC (2001)
Climate Shocks				
Sensitivity to location	a_0	1		authors
Sensitivity to scale	b_0	100		authors