A new family of Agent-Based Models and their application to high-end scenarios

Deliverable D5.2

December 2016

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IMPRESSIONS – Impacts and Risks from High-End Scenarios: Strategies for Innovative Solutions (www.impressions-project.eu)

Prepared under contract from the European Commission

Contract n° 603416
Collaborative project
FP7 Environment

Project acronym:	**IMPRESSIONS**
Project full title:	**Impacts and Risks from High-end Scenarios: Strategies for Innovative Solutions**
Start of the project:	01 November 2013
Duration:	60 months
Project coordinator:	NERC Centre for Ecology & Hydrology
Project website	www.impressions-project.eu

Deliverable title:	A new family of agent based models and its application to high-end climate scenarios
Deliverable n°:	D5.2
Nature of the deliverable:	Report
Dissemination level:	Public
WP responsible:	WP5
Lead beneficiary:	SSSA
Citation:	F. Lamperti, A. Mandel, M. Napoletano, A. Roventini, A. Sapio (2017). *A new family of agent based models and its application to high-end climate scenarios*. EU FP7 IMPRESSIONS Project Deliverable D5.2.
Due date of deliverable:	Month n° 38
Actual submission date:	Month n° 38

Deliverable status:

Version	Status	Date	Author(s)
1.0	Draft	16 December 2016	Lamperti, Mandel, Napoletano, Roventini, Sapio (SSSA & CNRS)
2.0	Final	20 December 2016	Lamperti, Mandel, Napoletano, Roventini, Sapio (SSSA & CNRS)

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Summary

The agent-based models (ABMs) described in this document use a complex systems perspective to analyse the economic impacts of high-end climate change and explore policy solutions to such impacts. They offer an alternative viewpoint with respect to traditional, computable general equilibrium Integrated Assessment Models (IAMs) for the analysis of coupled climate-economic dynamics and transitions towards greener production systems, and they provide complementary tools and information sources.

By their very nature, ABMs produce non-smooth patterns of economic growth resulting from disequilibrium interactions among heterogeneous and boundedly-rational agents. This contrasts with the optimal growth trajectories provided by standard IAMs. The presence of crises within the economic system (endogenous) is pervasive and can influence the development path of an economy and the very process of climate change. For example, crises might favour the relative competitiveness of certain technologies, the final emergence of new paradigms and, in turn, the transition towards a greener economy. Moreover, ABMs provide alternative perspectives on the climate-economy nexus. Green transitions can be studied by looking at the dynamics of technology adoption at the micro level and across multiple sectors. The links between firms' behaviour, financing sources, consumer preferences and the aggregate performance of the economy are naturally embedded in the models' structure. Furthermore, agent-based IAMs can incorporate disaggregated climate and weather shocks and, therefore, avoid the problems of aggregation faced in traditional modelling frameworks. Such a feature makes it possible to disentangle the effects of different kinds of climate shocks, ranging from capital or inventory destruction to labour productivity losses and energy efficiency deterioration.

Exploration of possible policy solutions showed a wide spectrum of results. Model simulations demonstrated that transitions to renewable energy technologies are unlikely without strong policy interventions. Moreover, the timing of policy interventions is crucial; only by moving the whole production of energy from fossil-fuel oriented to green technologies before 2025 was it possible to keep global increases in temperature below the 2°C target with reasonable confidence. Furthermore, price-oriented policy interventions aimed at inducing the green transition resulted in a non-linear effect that suggests that minor fossil-fuel taxes are largely ineffective. Alternatively, price-support policies, such as feed-in tariffs for renewable energy technologies, were found to produce an ambiguous effect on aggregate economic growth, with the final positive or negative impact depending upon specific features of the industry. In addition, we found evidence that both policy effectiveness and the likelihood of transitions depend on how climate damages affect individual economic agents. This result is amplified when extreme climate events are taken into account.

The ABMs developed within WP5 will be used in two main ways within the IMPRESSIONS project. First, they will serve as a laboratory to test multiple policy combinations, and second, they will be adapted to mirror the storylines characterising the WP2 socio-economic scenarios and employed to explore some of the characteristic pathways developed within WP4.

1. Introduction

Climate change is one of the most significant challenges humankind has ever faced. In order to develop adequate adaptation and mitigation strategies, policy-makers need reliable information about the co-evolution of ecological and socio-economic systems. While climate scientists have made enormous progress in understanding the physical mechanisms involved in climate change, there is a lively debate on the usefulness of existing economic models for the analysis of how rising temperature and more frequent and catastrophic weather events might impact the economy and, more generally, the whole of society.

Existing Integrated Assessment models (IAMs), which are widely employed by the Intergovernmental Panel on Climate Change (IPCC) to estimate socio-economic losses due to climate change and more generally the social cost of carbon (SCC, see e.g. IPCC, 2014), are fiercely criticised by an increasing number of scholars (see Pindyck, 2013; Stern, 2013, 2016; Weitzman, 2013; Revesz et al., 2014; Farmer et al., 2015; Balint et al., 2016, among many contributions). This is because IAMs provide an ad-hoc representation of the relationship between CO_2 atmospheric concentration and temperature increases, as well as the damage function linking climate change to socio-economic damages (Pindyck, 2013). Indeed, they usually underestimate or neglect the magnitude of risks, which could lead to the emergence of tipping points and non-reversibilities (Stern, 2016).

In economic models, the assessment of the cost of climate change is performed employing a social welfare function[1], which is grounded on questionable assumptions about the discount rate[2] and does not satisfactorily account for uncertainty. In particular, IAMs ignore possibilities of (small probability) catastrophic climate outcomes that would be expected to lead to huge economic damages. Moreover, IAMs are developed around the concept of market equilibrium, wherein a small number of representative firms and households maximise an expected utility or profit function. The assumption of the representative agent is questionable on both theoretical (Kirman, 1992) and empirical (Forni and Lippi, 1997; Heckman, 2001) grounds and it prevents IAMs from studying the dynamics of income and wealth inequality related to climate change and the possible policy responses. Similarly, the straitjacket of market equilibrium does not allow the effects of Schumpeterian technical change[3] to be studied, which could lead to the emergence of the radical and disruptive innovations necessary to support a green transition. Due to all the aforementioned problems, IAMs tend to underestimate the cost of climate change and the benefits resulting from the transition to a low carbon-emission economy (Stern, 2016). Given the current impasse, new approaches to modelling the co-evolution of climate change and economic dynamics are needed. In recent years, agent-based, network and system-dynamics models have been increasingly advocated as possible alternatives to more standard approaches (Balbi and Giupponi, 2010; Kelly et al., 2013, Balint et al., 2017; see also Annex I). In particular, agent-based models, such as those by Tesfatsion

[1] Social welfare functions represent people's preferences about social states that are usually expressed through levels of consumption and all other variables considered to affect the welfare of a society.

[2] The discount rate affects the value that economic agents assign in a given time to future quantities. It reflects the impatience of receiving a payoff. The larger the discount rate the lower the present value of a future payoff.

[3] Schumpeter argued that innovation and technical change bring about a process of "creative destruction" that continuously revolutionizes the economic structure from within, incessantly destroying the old one and replacing it with a new one.

and Judd (2006) and Fagiolo and Roventini (2012, 2016), have been promoted as constituting a valuable and promising approach (Smajgl et al., 2011; Farmer et al., 2015; Stern, 2016; Mercure et al., 2016; Balint et al., 2016).

ABMs consider the real world as a complex evolving system (see Farmer and Foley, 2009; Kirman, 2016, Dosi, 2012) 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 deduced by the simple aggregation of individual ones (Flake, 1988; Tesfatsion and Judd, 2006). The development of agent-based IAMs can overcome the issues plaguing IAMs (as described earlier) and support stakeholder participation and scenario plausibility exploration (Moss et al., 2001; Moss, 2002a). Indeed, the higher degree of realism of ABMs (Farmer and Foley, 2009; Farmer et al., 2015) allows policy-makers to be involved in the development of the model employed for policy evaluation (Moss, 2002b). For example, policy-makers have been involved in the elicitation of their preferences towards different paths of economic development, which have been subsequently employed to represent agents' heterogeneity in lobbying activities. Model results have finally been used to interactively develop policy options.

Hereby we introduce a novel family of agent-based and network models which aim to contribute to the debate outlined above. Such models can be used for a number of interrelated goals: (i) assessing the economic and social impact of high-end climate change; (ii) analysing how climate shocks might propagate within the production system; (iii) testing the effects of different climate and economic policies; and (iv) exploring the functioning of the economic system under varied climate and socio-economic scenarios.

2. A new family of agent-based models for climate-policy evaluation

A family of agent-based and network models has been developed to analyse the aggregate impact of climate change and risks due to climate policy (see Annex II for details). A number of innovations with respect to standard integrated assessment frameworks have been introduced, allowing the inclusion of heterogeneity among economic agents (e.g. firms, consumers, banks), out-of-equilibrium dynamics, complex interaction structures and micro-foundation of climate damages[4]. Our family of agent based and network models is composed of the following models:

1. DSK – a Dystopian Schumpeter Meeting Keynes agent-based model;
2. LAGOM;
3. EPN – Endogenous Production Network model.

These models are each briefly described in the following sections with links to specific details about the models and their applications in the Annex documents.

2.1. A Dystopian Schumpeter Meeting Keynes agent-based model

The Dystopian Schumpeter meeting Keynes (DSK) model is the main tool that will be used for the analyses of joint economic and climate dynamics that are carried out within the IMPRESSIONS

[4] Micro-foundation refers here to the fact that climate damages have been modelled to impact individual economic agents rather than aggregate variables (e.g. GDP).

project. It captures the co-evolution between a complex economy and the climate (more details on the model can be found in Lamperti et al., 2017 and Annexes III and IV). The economy and climate domains are linked via non-linear and stochastic feedbacks. DSK can be considered as the first agent-based integrated assessment model that can be employed to provide a detailed characterisation of the different micro and macro-climate shocks hitting the economy. The model allows the study of alternative ensembles of macroeconomic policies (e.g. innovation, industrial, fiscal and monetary policies) that can mitigate the impact of climate change, as well as sustaining the transition toward a green development path.

The DSK model builds on Dosi et al. (2010, 2013) and is composed of two vertically separated industrial sectors, whose firms are fuelled by an energy sector. Capital-good firms invest in Research and Development (R&D) and innovate to improve the performances of the machines they produce in terms of productivity, energy efficiency and environmental friendliness. Such machines are bought by consumption-good firms. Both energy and industrial sectors emit CO_2, whose concentrations in the atmosphere affect the evolution of the climate. Specifically, the carbon cycle is characterised by feedback loops in the relationship with the Earth's radiative forcing and the global mean surface temperature. The effects of an increase in the Earth's temperature on the economic system are captured by a stochastic disaster generating function. The disaster generating function changes over time according to temperature dynamics: under a warming climate, the probability of larger microeconomic shocks in labour productivity and firms' capital stock increases together with the mean size of the damage. Therefore, an increase in the Earth's surface temperature does not translate automatically in to higher aggregate damages as in most IAMs; rather, it modifies the structure of the stochastic process characterising economic growth at the micro level.

Firms in the capital-good industry produce machine tools using labour and energy. They innovate and imitate in order to increase both labour productivity and energy efficiency of the machines they sell to the consumption-good firms, as well as to reduce their own production costs. However, innovation and imitation are costly processes and firms need to invest a fraction of their past revenues in R&D activities. Technical change influences all of the three dimensions that characterise machines, namely, labour productivity, energy efficiency and environmental friendliness.

Consumption-good firms invest in machines, which are employed together with labour to produce a homogenous 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 capital markets. Firms access firstly their net worth and if the latter does not fully cover total production and investment costs, they borrow external funds from the bank. However, firms have limited borrowing capacity; the ratio between debt and sales cannot exceed a maximum threshold depending on the firms' past sales. As a consequence, credit rationing might endogenously occur.

Energy generation is performed by a profit-seeking, vertically-integrated monopolist through heterogeneous power plants using green and dirty technologies. The energy monopolist produces and sells electricity to firms in the capital-good and consumption-good industries using a portfolio of power plants, which are heterogeneous in terms of cost structures, thermal efficiencies and environmental impact. Green plants convert renewable sources of energy (such as wind, sunlight, etc.) into electrical power at a null marginal production cost and produce no greenhouse gas emissions. However, large fixed costs are necessary to build up new green plants. Conversely, the stock of fossil-fuelled plants can be expanded at virtually zero fixed costs, but energy generation via dirty power plants involves positive marginal costs reflecting either the price of fossil fuels or extraction costs. Technical change occurs along both the technological trajectories (green and dirty, see Dosi, 1988) and improves plants' efficiency and environmental friendliness.

Finally, a climate box links CO_2 emissions with atmospheric concentrations of carbon and the ensuing dynamics of the Earth's mean surface temperature. These relationships are modelled in a non-linear way through a core carbon cycle characterised by feedbacks as in Sterman et al. (2012). The climate box avoids a complex and detailed description of the physical and chemical relations governing the evolution of the climate, while capturing its major features, including feedbacks that might give rise to non-linear dynamics. In particular, our carbon cycle is modelled as a one-dimensional compartment box based on Goudriaan and Ketner (1984) and Oeschger et al. (1975). Atmospheric CO_2 is determined on a yearly basis by the interplay of different factors, which account for anthropogenic emissions, exchanges of CO_2 with the oceans and net primary production.

The model allows the study of alternative ensembles of macroeconomic policies (e.g. innovation, industrial, fiscal and monetary policies) that can mitigate the impact of climate change, as well as sustaining the transition toward a green development path.

2.2. The LAGOM model

The LAGOM model incorporates agent-based dynamics into the standard Arrow-Debreu general equilibrium framework (see Annex II for details). It considers an economy with discrete periods of time, an arbitrary number of commodities and one kind of labour. The usage of commodities is not, a priori, specialised and each can potentially be used as fixed capital, as intermediary consumption or for final consumption. The economy is populated by a finite number of firms and households, a government and a financial system. The households provide labour and consume (non-durable) commodities. The firms are partitioned into sectors according to the goods they produce using heterogeneous capital and labour. A multiple-regions structure is also allowed. The government levies an income tax and provides unemployment insurance. The financial system sets the interest rate according to a Taylor rule[5], collects savings from households and grant credits to firms for investment. More precisely, agents are endowed with two main types of state variables: (i) stocks such as goods, capital, labour, money, savings, debt; and (ii) strategies such as prices, production targets, production technologies, reservation wages, consumption habits, interest rates. These stocks and strategies evolve during a sequence of micro-economic interactions that, in aggregate, give rise to macroeconomic dynamics and structural change.

The model can be used to explore the dynamics of consumption, production and emissions, with particular attention given to the role of structural change and regional heterogeneity.

[5] The Taylor rule determines how a Central Bank fixes the interest rate level. Usually it predicts that the interest rate should respond to changes in output, inflation and other variables characterising the state of the economic system.

2.3. The Endogenous Production Network model

The Endogenous Production Network (EPN) model is an agent-based model where technological evolution is modelled in detail through the evolution of production networks (see Annex V for details). These networks provide a detailed description of the technological and commercial relationships between firms and can easily be mapped to an input-output table. On the one hand, they form the structure that determines economic dynamics in the short-run and, on the other hand, their evolution reflects the long-term impacts of competition and innovation on the economy.

Accordingly, once the network is defined in this model, the dynamics of prices and output follow from the application of simple behavioural rules. Conversely, the evolution of the network reflects the long-term dynamics of the economy driven by competition and innovation processes. Competition materialises via redirections (rewiring) of relationships between firms which hence induces a "horizontal" evolution of the network. Innovation and technological change, which form the core of our model, materialise both via radical (product) innovation and incremental (process) innovation. Radical innovation occurs through the discovery by firms of new technological paradigms that lead to increasingly efficient products. Process innovation materialises, within a technological paradigm, through diversification of the input mix. The interplay between these processes drives the evolution of the network; process innovation through diversification leads to increasing connectivity among firms, while radical innovations might render obsolete a very mature technology and hence induce a decrease in connectivity. The input-output structure of the model evolves accordingly.

The model allows analysis of impacts on the long-term evolution of the production network brought about by:

1. Mitigation policies (e.g. feed-in tariffs, see Section 3)
2. Long-term climate impacts such as changes in agricultural yields.

3. Evaluation of transitions, climate damages and policy measures

The three models introduced in Section 2 allow a variety of issues linked to the joint dynamics of climate and economic variables and the ability to account for their complex interaction to be studied. The following sections summarise the main results emerging from some simulation experiments (full details and further discussion of the simulations are given in Annexes II to V).

3.1. Evaluation of transitions

The analysis of transitions from fossil-fuel to low-carbon technologies is a fundamental step in the understanding of the triggers, likelihood and impact of moving towards a different production system under different starting scenarios. The DSK model constitutes a viable platform to perform such an analysis.

In particular, the DSK model accounts for endogenous technical change both in the industrial and the energy sectors. In the latter case, decisions on energy production are made on the basis of generation costs. Revenues are then partially reinvested in R&D activities and, specifically, there is a parameter controlling the share of R&D spending in green and fossil-fuel technologies. By simply linking this parameter to the previous sales of dirty and green energy, it is possible to study the process of diffusion of low-carbon energy technologies, together with the aggregate impacts of such a phenomenon on the economy and the climate. We assume that the share of R&D investment in green (or dirty) technologies is equal to the quota of the previous period energy sales from that technology. This reflects the common idea that market size might play some role in shaping the direction of technical change and that investments tend to cumulate on the prevailing areas. In particular, we notice that, under endogenous R&D investment decisions, the model shows two statistical equilibria which, loosely speaking, correspond to two kinds of behaviour that are statistically different. In the first case, we find a carbon-intensive lock-in where the share of energy produced with renewable technologies approaches zero and, after having reached this bound, stays there until the end of the simulation. In the second case, a transition to green energy technologies occurs with this persistently dominating the market.

Numerical simulations provide a number of relevant key results, including the following:

- **Under business-as-usual, the likelihood of transition is remarkably low**. We find that endogenous transitions towards the equilibrium where green energy technology dominates the market are possible but, in the absence of policy intervention, the likelihood of such an event does not exceed 18%. This result is based on assuming zero climate damages.
- **The presence of climate damages can potentially increase or reduce the likelihood of transitions**. We consider climate damages in two different ways. Firstly, we take the standard aggregate perspective embraced by the majority of IAMs. Secondly, heterogeneous climate damages that target labour productivity or energy efficiency are considered. In the first case, the likelihood of transition is exactly the same as the case of no damages, since they only affect aggregate potential output. In the second case, we find that labour productivity shocks might increase the likelihood of transitions (with respect to the case of aggregate damages), while the opposite happens for energy efficiency shocks. The main channel of these effects is represented by the size of the final demand for energy (see Annex IV for details).
- **The price of fossil fuels non-linearly influences the likelihood of transition**. We find that an increase in the initial price of fossil fuels might increase the likelihood of a transition. However, such an effect is largely non-linear. Given the initial backwardness of clean technologies' productivity (Acemoglu et al. 2012; Lamperti et al. 2015) and the cumulative nature of the technical change process, small variations of the fossil fuel price have a surprisingly low impact on inducing the transition, while for moderate/high increases the likelihood increases substantially. This result supports the idea that policy intervention, in this case aimed at increasing the cost of fossil fuels, needs to be substantial in order to significantly affect the environmental sustainability of the production system.
- **Climate change can be kept under the 2°C target only if the transition occurs before 2025**. We find that the timing of the transition is crucial in determining the level of temperature anomaly at the end of the century. Our results point to a transition that should take place between 2025 and 2030 in order to meet the 2°C target. We also find that there is a reasonable likelihood that global mean temperature will rise above 3°C if the transition materialises after 2075.

3.2. Climate damages and impact assessment

One of the advantages brought about by the use of our family of agent-based models is the provision of a genuine micro-foundation of climate damages (see Annex II for details). In the majority of integrated assessment exercises (see Clarke et al, 2009 and Nordhaus 2014), damages are both estimated and projected as the percentage of GDP lost because of the effects of climate change. However, typically nothing is said about the channels through which these effects might arise. By contrast, the DSK model allows the analysis of the aggregate impact of climate shocks that might affect a variety of aspects characterising economic agents, whether they are firms, workers or individuals, as well as industrial and energy plants. Furthermore, we provide a stochastic description of damages which are sampled from a non-stationary distribution allowing for low-probability but large-impact events. Using DSK as a laboratory to test the effects of heterogeneous climate shocks we have obtained a variety of results that are summarised here:

- **Aggregate climate impacts largely depend on the channel through which they affect economic agents**. Climate shocks targeting different variables (labour productivity, energy efficiency, capital stock, inventories) have a diverse impact on economic dynamics with labour productivity and capital stock shocks producing the largest harm to the economic system. For instance, under labour productivity shocks the average growth rate of the economy is almost one third of that simulated in the absence of climate damages; on the other hand, targeted damages to energy efficiency and firms' inventories reflect a slight impact on economic growth but exacerbate instability.
- **Agents' interconnections amplify climate damages**. We find that climate shocks have a much more catastrophic impact on the economy in our model than in computable general equilibrium (CGE)-based IAMs, despite the average size of climate shocks being comparable (see Nordhaus, 2014 and Annex III). In some cases, when shocks are combined, the difference is dramatic. The more catastrophic impact of climate change in the DSK model compared to 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 the different channels interlinking economic behavior of the different agents.
- **Under some scenarios the economy might end up in a stagnating and/or highly instable pattern of growth**. The effects of climate damages are highly non-linear over time and affect not only variables in terms of levels (e.g. GDP, unemployment), but also in terms of growth rates. We find that labour productivity shocks might even induce a negative growth pattern by the end of the century, while capital stock shocks lead to a pattern with positive long-term growth which is significantly punctuated by severe crises and recessions.

3.3. Policy exercises

The flexibility of the modularity of ABMs (Fagiolo and Roventini, 2012, 2016; Balint et al., 2016) is beneficial for studying how different policy combinations can promote (or not) the transition to sustainable growth paths characterised by green production and low CO_2 emissions. They also constitute a valuable 'laboratory' for studying the effects of policy inaction and exploring the dynamic effectiveness of a policy instrument introduced at different points in time. Finally, the higher degree of realism of the models (see Section 2) combined with their inclusion of economic structure and climate dynamics facilitate interactions with policy-makers and stakeholders in co-designing the policies to be tested (Moss, 2002b). Table 1 collects a non-exhaustive list of the policy exercises that are available; they have been divided across models in order to show that similar policy experiments might be tested using more than one modelling framework and results coupled to better disentangle the main issues at hand.

Table 1: Policy exercises available in the DSK, LAGOM and EPN models.

Climate and energy policy	Macro policy	Industrial policy
DSK		
Carbon Tax	Fiscal Policy	Standards
Command and Control Quotas	Green Quantitative Easing	Directed R&D Policies
Fossil fuel Taxes	Green Bonds	Reform to the Patent System
Minimum share of renewable energy		
LAGOM		
Energy Taxes and Subsidies	Labour Market Policies	
Coordination of Investments	Monetary Policy	
Expectation Management		
EPN		
Feed-in tariffs	Fiscal Policy	R&D Policies
		Standards

Here we collect some insights emerging from two different model experiments involving some of the policy instruments included in Table 1:

- **Carbon tax in the DSK model:** We find that the carbon tax has an overall positive effect on long-term growth and emissions intensity. However, it significantly interacts with the assumed scenario characterising climate damages. In particular, under climate shocks affecting labour productivity and capital stock it is shown to be largely insufficient (we consider carbon taxes ranging from 10 to 30 monetary units per tCO_2), pointing to the need of a more aggressive policy mix. Alternatively, in those scenarios where shocks target inventories or energy efficiency, it successfully triggers the transition towards more sustainable production systems and prevents the economy from suffering large climate damages. Summing up, we find that carbon tax effectiveness is largely dependent on the structure of climate damages, supporting the need for greater attention to their empirical analysis.

- **Feed-in tariffs and preferential market access in the EPN model:** The EPN model has been employed to compare the effects of price-based (feed-in tariffs) and quantity-based (preferential market access) policy instruments on economic growth. Results show that only the price-support policy has an impact on firms' survival probabilities and hence on output. This suggests that price-support measures have, in our framework, a stronger impact on the competitive position of firms. Moreover, the market-support policy only shifts demand within the economy while the price-support policy provides, at the aggregate level, a subsidy to the economy by financing externally the price reduction for radical innovators. This subsidy can yield a demand-push and indirectly trigger multiplier effects. However, effects on aggregate output is ambiguous; depending on the features of the energy industry there might be both reduced and slightly increased aggregate growth when a price support based mechanism is introduced. These results support cautiousness in the design of quantity- or price-based mechanisms to induce a large use of renewable energy, whose effect might not coincide (see also Lamperti et al., 2015) and depend on the structure of the industry.

4. Relationship with the other parts of the project

The family of models described here constitutes one of the main products from WP5. They provide a valuable resource for studying the climate-economy system. Two complementary applications are possible in IMPRESSIONS. Firstly, models can be calibrated on comparable conditions with respect to the real climate-economic system and then run to test the effects of policy interventions or system features (such as the type of climate shocks or firms' ability to innovate). Secondly, models can be approximately initialised and configured to represent the scenarios developed in WP2 based on the downscaled Shared Socioeconomic Pathways (SSPs; see Deliverable D2.2) and used to (i) project the evolution of the economic system within the scenario, and (ii) analyse some characteristic mitigation pathways for each scenario emerging from WP4. With respect to this latter application, the models will be employed to show the differences among the various worlds underlying each socio-economic scenario on the basis of emissions intensity, presence or absence of climate policy or individual pro-environmental attitude (BAU vs. environmental-caring attitude), inequality and distribution of wealth and likelihood of transition to renewable energy sources.

In particular, the model will be used within each SSP scenario for the European case study as follows:

- **SSP 1** – To simulate socio-economic dynamics within such a scenario, models will mainly focus on energy-efficiency and possible trajectories of technological change affecting this dimension.

- **SSP 4** – Within this scenario, the main issue to be analysed will be the introduction and diffusion of green technologies, both in the industrial and energy sectors. Moreover, experiments on the initial level of functional inequality in the economy can be included to better explore the link between this aspect and the pace of green technological advancement.

- **SSP 5** – Within this scenario the focus of the analysis will be on the introduction of carbon taxes/carbon pricing at different points in time, letting policy interventions interact with path-dependency in the socio-economic dynamics.

- **SSP 3** – Application of the family of ABMs for this SSP is more difficult and needs to be further explored. While the models might account for the severity of climate extreme events and the level of inequality in the economic system, they are not fully equipped to characterise the circular-economy structure.

5. Acknowledgments

We thank Thomas Balint, Stanislao Gualdi and Irene Monasterolo for relevant comments, suggestions and practical help in the development of the family of models described in this document. More detailed acknowledgements referring to single models are included in the Annexes.

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7. Annexes

Five annexes are included:

I. A survey paper on agent-based and network models for climate change and climate policy analysis: “Complexity and the economics of climate change: a survey and a look forward” as published in Ecological Economics [from pag 18 of this document].
II. A paper describing the family of models that has been developed: “Towards agent-based integrated assessment models: examples, challenges and future developments” as submitted to Regional Environmental Change. [from pag 55 of this document]
III. A paper describing the investigation of macroeconomic and climate dynamics by means of the DSK model: “Faraway, so close: coupled climate and economic dynamics in an agent-based integrated assessment model” as submitted to Ecological Economics. [from pag 86 of this document]
IV. A draft document describing the application of the DSK model to the issue of energy transitions: “A walk on the wild side: transition to sustainable growth in an agent-based

integrated assessment model" to be submitted to a relevant journal. [from pag 132 of this document]

V. A paper describing the structure of the endogenous production network model and some policy application: "Endogenous growth in production networks" as published in the Journal of Economic Dynamics and Control. [from pag 163 of this document]

Complexity and the Economics of Climate Change: a Survey and a Look Forward

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July 8, 2016

Abstract

We provide a survey of the micro and macro economics of climate change from a complexity science perspective and we discuss the challenges ahead for this line of research. We identify four areas of the literature where complex system models have already produced valuable insights: (i) coalition formation and climate negotiations, (ii) macroeconomic impacts of climate-related events, (iii) energy markets and (iv) diffusion of climate-friendly technologies. On each of these issues, accounting for heterogeneity, interactions and disequilibrium dynamics provides a complementary and novel perspective to the one of standard equilibrium models. Furthermore, it highlights the potential economic benefits of mitigation and adaptation policies and the risk of under-estimating systemic climate change-related risks.

Keywords: climate change, climate policy, climate economics, complex systems, agent-based models, socio-economic networks.

JEL: C63, Q40, Q50, Q54.

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1 Introduction

This paper provides a survey of the economics of climate change from a complexity science perspective and underlines the challenges ahead for this line of research.

Mitigation and adaptation to climate change represent governance challenges of an unprecedented scale because of their long-term horizon, their global nature and the massive uncertainties they involve. Against this background, equilibrium models generally used in Integrated Assessment Models (IAM) represent the economy as a system with a unique equilibrium, climate policy as an additional constraint in the optimization problem of the social planner and consider the uncertainty of climate-related damages to be predictable enough to be factored out in the expected utility of a representative agent. There is growing concern in the literature that this picture might convey a false impression of control (see Pindyck, 2013; Stern, 2013, 2016; Weitzman, 2013; Revesz et al., 2014; Farmer et al., 2015, among many contributions) and that IAMs might underestimate both the cost of climate change and the benefits resulting from the transition to a low carbon-emission economy (Stern, 2016).

Network and agent-based models have been increasingly advocated as alternatives fit to handle out-of-equilibrium dynamics, tipping points and large transitions in socio-economic systems (see e.g Tesfatsion and Judd, 2006; Balbi and Giupponi, 2010; Kelly et al., 2013; Smajgl et al., 2011; Farmer et al., 2015; Stern, 2016; Mercure et al., 2016). These classes of models consider the real world as a *complex evolving system*, wherein the interaction of many heterogeneous agents possibly reacting across different spatial and temporal scales give rise to the emergence of aggregate properties that cannot be deduced by the simple aggregation of individual ones (Flake, 1988; Tesfatsion and Judd, 2006). The development of agent-based integrated assessment model can overcome the shortfall of equilibrium models and ease stakeholder participation and scenario exploration (Moss et al., 2001; Moss, 2002a). Indeed, the higher degree of realism of ABMs (Farmer and Foley, 2009; Farmer et al., 2015) allows to involve policy makers in the process of the development of the model employed for policy evaluation (Moss, 2002b).

In this paper we present a critical review of the existing literature about complex system approaches to the economics of climate change, focusing in particular on agent-based models. Even if this research line is still in its infancy, it has already produced valuable insights into the functioning of economies facing climate and environment issues. We identify the main results, policy implications, limitations, and open issues that future research efforts should address. Moreover, we consider how the discussed contributions might serve as building blocks for a new generation of models.

We distinguish four main fields relevant to the economics of climate change in which complex system models have been fruitfully applied.[1] The *first* consists in the analysis of climate negotiations and coalition formation (cf. Section 2). There, we show that out-of-equilibrium dynamics, learning and influence among and within heterogeneous actors are pivotal to get a full understanding of the barriers and the potential paths to cooperation that are key concerns for international climate-policy negotiations like the recent Paris agreement.

Second, we concentrate on agent-based models studying the macroeconomics of climate change (see Section 3). These models study in particular how the interactions between heterogeneous agents affect the aggregate performance of an economy facing increasing climate risks. They have shed new light on the different role that micro-level climate and weather shocks have on macroeconomic dynamics, on the risk stemming from climate policy and the profound interconnectivity affecting the overall system. The next milestone in this field is the development of the first generation of agent-based integrated assessment models.

Third, we consider the functioning of the energy sector, which is by far the largest emitter of greenhouse gases globally (see Section 4). In this field, deregulation (especially in electricity market) has pushed modelers to shift their attention from monopoly and oligopoly settings to complex structures characterized by heterogenous players interacting in energy markets with different institutional settings. ABMs have been employed to study pricing rules, market power in complex institutional settings, the evolution of financial networks and networks of influence in the energy industry. Finally, agent-based models have also been employed to analyze the comparative effects of climate policies on electricity prices, the energy technology mix and energy efficiency.

Fourth, agent-based models have been largely employed to study the process of technical change and innovation diffusion, which lie at the core of the structural change needed for the transition to a low-carbon economy (cf. Section 5). Herein, an adequate characterization of the Knightian uncertainty (Knight, 1921) affecting search for innovations, a correct accounting of path dependencies in technological development and a strong emphasis on the role that interaction structures and institutions play on the selection landscape are essential to correctly analyze conditions that might favor (or impede) shifts from one technological paradigm to an alternative one (see Dosi and Nelson, 2010, for a comprehensive discussion on innovation and technical change from an evolutionary perspective).

Finally, we provide a general critical assessment of the adoption of agent-based and network models to study the micro and macro economics of climate change (see Section 6). In particular, we will stress the current weaknesses and the potential research directions to further improve such models in order

[1] We do not consider land-use agent-based models. This increasing stream of literature, where ABMs are largely applied, has its own specific features and would deserve a more extensive and autonomous treatment. See Matthews et al. (2007) for a survey on the topic and Filatova et al. (2013) for a recent discussion.

Figure 1: Global emissions by country and sector.

(a) Global emissions by country.

(b) Global emissions by sector.

Note: Panel 1a shows 2011 global CO_2 emissions from fossil fuel combustion and some industrial processes by country. Source: Boden et al. (2015). Panel 1b shows global greenhouse gas emissions by economic sector. Source: IPCC (2014).

to address the complex interconnections between economic dynamics and climate change.

2 Coalitions formation and climate negotiations

Effectiveness and stability of international climate agreements are pivotal to the fulfilment of the long run objectives of decoupling output and emissions growth and, ultimately, containing rise in global mean surface temperature. Figure 1a shows that global emissions are quite fragmented overall but, on the other side, few large players account for more than half of the total value. This fact highlights the importance of international cooperation, where agreements between major players is required to get substantial effects in the short run. In line with the seminal contribution of Barrett (1994), the main outcome of the game-theoretic literature on the formation of international environmental agreements has been that it is extremely difficult to sustain global cooperation among a large number of strategic actors solely on the grounds of environmental benefits. This negative result is somehow at odds with the mild successes obtained on climate change mitigation through the Kyoto protocol and, more recently, the Paris agreement. A commonly accepted explanation for the presence of this gap in the theory is that a static one-shot game model with a large number of homogeneous players can possibly serve as a benchmark but does not account for the full complexity and the specific context of international agreements such as those pursued in climate negotiations. Therefore, the literature has developed in two complementary directions that tried to account respectively for (i) the multi-dimensional and heterogeneous aspects of actors' strategies and (ii) the dynamic, "local" and/or hierarchical nature of the interactions between agents.

Within the equilibrium-centered game-theoretic literature, these developments have led to positive results about the stability of grand coalitions when effects due to networks (see e.g Benchekroun and Claude, 2007), heterogeneity (e.g McGinty, 2006) or more simply transfers (see e.g Hoel and Schneider, 1997) are accounted for. A wide literature that linked pay-offs in the "emissions game" to the outcome of integrated assessment models (IAMs) also developed. In particular, Lessmann et al. (2015) compare stability results for climate agreements from five different IAMs and find that, across all models, heterogeneity of regions improves incentives to participate.

The equilibrium-centered literature focused only on the stability issue relying on very strong assumptions about the rationality and the stationarity of preferences of state actors. As a consequence, it remained silent about the barriers and the potential paths to cooperation that are key concerns for policy applications. In order to get a full understanding on them, one needs models accounting for out-of-equilibrium dynamics, learning and influence among and within state actors.

2.1 Learning and cooperation

A first step in that direction has consisted in investigating behavioral and institutional aspects of learning and cooperation in game-theoretic settings. Breton et al. (2010) considers a set of countries that can be either signatory or non-signatory of an emission reduction agreement. Non-signatory countries maximize their individual welfare, while signatory countries maximize their joint welfare and punish non-signatories (e.g through trade sanctions). The proportion of signatory countries is then assumed to follow a replicator dynamics. Numerical solutions show the emergence of multiple equilibria corresponding to no-cooperation and either partial or full cooperation. Phase transition mechanisms underline the existence of thresholds in terms of the stock of emission and/or number of signatories above which the system eventually reaches full cooperation. Smead et al. (2014) represent negotiations as an N-player bargaining game where countries/players bargain about their percentage emission reduction. The agents are adaptive and update their pledges on the basis of expectations formed using a variant of fictitious play. Cooperation and disagreement are both equilibria of the underlying game as well as attractors of the ensuing dynamics. The authors argue that a potential obstacle to successful negotiations not related to the stability of feasible solutions is *"whether learners can find these solutions and avoid disagreement equilibria"*. They also point out that the larger the number of players, the less likely cooperation emerges. Interestingly, however, they show that prior/sequential agreements between subsets of countries increase the chance of reaching a global solution.

Both contributions put emphasis on the progressive formation of climate clubs as pathways for efficient mitigation policy (see e.g. Nordhaus et al., 2015; Heitzig et al., 2011). Yet, the focus on states as the only relevant actors as well as the uni-dimensionality of the perspective limit the new insights that can emerge from such models. They are also silent about the formation and the evolution of preferences and contrast with the emphasis put by Putnam (1988) on the linkages between national and international politics. Moreover, in the context of climate policy, they are at odds with Jaeger and Jaeger (2011), who argues that the consensus on the objective of limiting global warming to 2 degrees resulted from a combination of physical, environmental, economic, diplomatic or ethical arguments, which let the 2 degrees target emerge as a focal point on the basis of which actors can anticipate and make decisions. As emphasized by Janssen and Ostrom (2006) and Lempert et al. (2009), agent-based models are particularly well-fitted for such multilevel, multi-agents decision-making problems.

2.2 The role of interactions

From a macro-level perspective, Courtois and Tazdaït (2007) subsume the standard game-theoretic approach to international environmental agreements by considering that agents and countries employ the outcome of a game-theoretic analysis as an expert's recommendation, but actually determine their policy in a sequence of bargaining interactions with their peers. During such interactions, agents can either imitate, persuade or dissuade each others to cooperate to climate change mitigation. Depending on the propensity of countries to imitate and on their bargaining power, different stable configurations emerge in the model corresponding to different levels of international collaboration. Such results extend the one of the standard game-theoretic literature, by shedding light on the behavioral determinants of failure and success in negotiations.

A second series of contributions has focused on the bottom-up formation of climate policies through the interactions of micro-level agents. In the battle of perspectives of Janssen and de Vries (1998), three types of agents (Individualists, Hierarchists and Egalitarian) coexist. They differ in their "world-view", which captures their beliefs about climate sensitivity, the cost of mitigation and its climate-related impacts. They also have different preferences about macro-economic and climate policy objectives. The economy is actually governed according to a weighted average of the preferences of the population. As the system evolves through time, world-views might turn out to be more or less accurate, and their share in the population evolves according to their fitness. The authors emphasize that these adaptive dynamics can yield trajectories that differ massively from those induced by "utopia" (in which there is a unique well-defined social preference and correct expectations) and therefore one needs to account for bias and errors in the definition of long-term emission scenarios.

Isley et al. (2015) consider firms that lobby a government for more or less stringent climate policies (e.g carbon price or carbon tax). Beneath the strategically determined climate policy, the economic pathway is defined following the agent-based dynamics introduced in Dosi et al. (2010). In this framework, the authors investigate the efficiency of different institutional architectures for climate policy. They emphasize that a necessary condition for an effective policy is the emergence of a stable constituency in favor of a stringent climate policy which, in turn, requires a steady stream of technological innovation to maintain firm heterogeneity. This series of linkages highlights the importance of accounting for the interdependencies between, inter alia, the economic, industrial and political spheres and how this is made possible by agent-based modeling.

Relatedly, Earnest (2008) and Greeven (2015) aim to provide a comprehensive perspective on the political issues linked to international negotiations by implementing an agent-based version of Putnam (1988) two-level games, with negotiators and their constituencies as agents. Earnest (2008) considers negotiators who ought to coordinate on an international (environmental) agreement that is acceptable by their constituencies. Both negotiators and their constituencies have evolving preferences. Negotiators are sensitive to the preferences of other negotiators and of their own constituencies. Constituencies also influence each other transnationally. Such a model seems to better account for the complexity of climate negotiations and allows to study path histories that are important to multiple equilibria games. The main findings of the model are that factors favoring coordination are (i) a large number of negotiating parties, (ii) dense transnational influence, (iii) fast-evolving preferences, (iv) sensitivity to constituencies preferences, and (v) relative independence from other negotiators' preferences. Similarly, Greeven (2015) uses the two-level game framework of Putnam, but further adds to the model uncertainties about the probability of climate-related impacts and the awareness of the public about such risks. The model is then used to identify consistent and plausible narratives on the pathways leading to the emergence of climate change mitigation. In that, it highlights the potential usage of agent-based modeling for scenario discovery (see also Rozenberg et al., 2014; Gerst et al., 2013).

2.3 Open issues

Being grounded on heterogenous, interacting actors, agent-based models offers a methodology both to gain insights about the workings of the international negotiation process and to build scenarios about potential long-term trajectories. Downing et al. (2001) also emphasize the potential of agent-based model for stakeholder engagement in the design of climate policies and puts forward as a prototype of such an approach an agent-based model of water management in the Thames region of England (see also Tesfatsion et al., 2015). However, to be extended at a broader scale, this approach requires to integrate climate negotiation models with ABMs representing the evolution of the economy over the long term. In that, the macro agent-based models presented in the next Section could constitute a useful starting point to link climate negotiations and macroeconomic dynamics.

3 Climate-change macroeconomics

Studying the co-evolution between climate change and macroeconomic dynamics poses non trivial challenges. First the lack of long macroeconomic time series makes difficult to empirically explore the inter-dependences between the two systems.[2] Second, climate and macroeconomic dynamics occur at different time scales. Third, the poor understanding of human responses to warmer climates and extreme weather events renders difficult the characterization of climate damages.

Given the foregoing issues, one of the main advantage of macro ABM is to allow for a micro-level representation of the interactions between climate change and economic dynamics (as emphasized in particular by Moss, 2002a and, more recently, Farmer et al., 2015). Indeed, the agent-based approach can better account for the out-of-equilibrium dynamics shifting the economy from a business-as-usual to a green growth path. Moreover, network and agent-based models can provide a more accurate representation of climate-related damages considering distributional issues and the role of system connectivity. Relatedly, complexity-based models can be employed to study how climate change risks impact on financial market dynamics. Finally, the fast pace at which ABMs have blossoming in the last years has lead to the development of a new generation of agent-based integrated-assessment models (Lamperti et al., 2016).

3.1 Macro-climate ABMs

With respect to the analysis of the energy transition, a pioneering contribution is this of Robalino and Lempert (2000) (see also Brouwers et al., 2001), which use a simple ABM to test the effectiveness of "carrots" (incentives to technology adoption) vis-à-vis that of "sticks" (carbon taxes and emissions trading, which increase the price of high-emitting technologies for all users) in pushing the economy towards a low-carbon development path. They show that coupling carbon taxes and technology incentives is the best approach to cut greenhouse gas emissions. Their result is mainly driven by the heterogeneity of consumers' preferences and expectations.[3] Notwithstanding these interesting insights, the model is too simple to account for multiple equilibria and endogenous growth. This limitation might be particularly relevant in the design of climate policy. As suggested by Jaeger et al. (2013), policy makers should reframe the problem of climate change from a zero-sum game to win-win solutions,

[2]For example, in Dell et al. (2012), the authors are constrained to employ a relatively short sample of 50 years and find that temperature shocks seem not to affect developed countries.

[3]The superiority of combining taxes and subsidies with respect to solutions based on a single policy prescription has also been obtained in a general equilibrium model by Acemoglu et al. (2012).

i.e. designing mitigation measures that are beneficial for the economy. In a framework where several equilibria are possible, the mitigation problem is not linked to scarcity but rather to a coordination issue (Jaeger, 2012).

One of the first attempts to dynamically model a complex economy together with a climate module can be traced back to the LAGOM model family (Haas and Jaeger, 2005). Heterogeneous households and producers face the risk of climate-related damages and are offered insurance contracts. An "expectation manager" helps insurers and households to up-date their expectations on the basis of new observations. Finally, the model is characterized by the presence of a market module where interactions involving households and insurers determine weather insurance prices through. LAGOM operates at multiple time scales: market interchanges occurs much faster than climate change, and industrial production takes place at intermediate frequencies. The flexible accounting for different time scales is an advantage of ABMs vis-á-vis traditional IAMs, which usually consider yearly equilibrium adjustments both in the economic and climate system.[4] Mandel et al. (2009) and, more recently, Wolf et al. (2013) have further extended the LAGOM model to simulate a growing economy with the possibility of specifying different interacting economic areas and to study the properties of economic growth as emerging from spatially explicit production networks. In each region, energy is produced within specific sectors with carbon emissions as a by-product. The model could then be used to test different mitigation policies.

Economic dynamics mainly affects climate change via the degree of environmental friendliness of production technologies, i.e. the amount of GHG emissions stemming from production. In general, production might involve goods, capital and energy. There are few sufficiently sophisticated agent-based models to deal with all these three aspects. Beckenbach and Briegel (2010), for example, limit themselves to the study of a generic production process, which is decomposed across different but not well-specified sectors. In a Schumpeterian setting, growth is triggered by firms' innovation and imitation strategies, and emission dynamics depends on two exogenous parameters governing the diffusion of low-carbon innovations and their quality. Gerst et al. (2013) propose an agent-based model that *completely* endogenizes the process of technical change leading to the diffusion of less emission-intense machines. Drawing on the Keynes+Schumpeter model (K+S, cf. Dosi et al., 2010), they study a complex economy composed of two vertically related industrial sectors and an energy production module, where competing technologies can be used to generate energy that is subsequently distributed through the system. The model is calibrated on US macroeconomic data and simulated until the end of the century to study different carbon tax recycling schemes. They find that only a policy focused on subsidies to carbon-free technology oriented R&D allows a swift transition away from "dirty" energy technologies, and, in turns,

[4] Or, in a variety of cases, adjustment periods of 5 years (see e.g. Nordhaus, 1992; Bosetti et al., 2006).

to higher economic growth. Similar results are found in the ABM developed by Rengs et al. (2015).

The major issues addressed in the contributions described so far is the identification of possible growth trajectories for both the economy and aggregate emissions, and in the adoption of fiscal policy (mainly carbon-taxes and subsidies) to direct the system towards some of these directions. The value added consists in the analysis of growth as a stable phenomenon emerging from an ecology of heterogeneous agents, whose different reactions to policies and uncertain environments can move the economy along trajectories that cannot be deduced otherwise. However, a key element is missing the picture. Indeed, the relationship between macroeconomic properties and the climate is explored in a single direction. The feedbacks that agents (firms, energy-production plants, households, etc.) receive from a increasing and possibly more volatile temperatures have been generally ignored. Building on the baseline setting provided by Dosi et al. (2010), Isley et al. (2013) construct a prototype for a hybrid agent-based integrated assessment model that could support the design of a government's regulatory climate policies. The authors underline the usefulness of the approach in analyzing transformative solutions, that is, in examining how measures intended to reduce GHG emissions can trigger market-induced transformations, which, in turn, affect the government's ability to maintain its policy in an environment where agents affect the climate and receive back climate-related damages. However, in the latter framework, the climate system is left out of the picture and damages are linked to emissions, not to the average surface temperature. Moreover, environmental damages are modeled like in standard IAM (see e.g. Nordhaus, 1992, 2008; Tol, 1997) as aggregate cuts to potential GDP levels.

3.2 Climate shocks, damages and system connectivity

In most Integrated Assessment Models, climate damages are accounted for by an *ad hoc* damage function that impacts output (at the sectoral or the macro level) as a function of temperature increases brought about by GHG emissions (see the discussion in Pindyck, 2013). This approach ignores the propagation of shocks and the feedbacks that might relate damages to different sectors. Moreover, as most IAMs do not allow for agent heterogeneity, they entirely overlook distributional issues linked to climate damages.

Against this background, one of the characterizing features of complex systems lies in their representation of real phenomena as emerging from the interactions of heterogeneous agents. This approach alllows to model the emergence of aggregate damages from micro shocks in production, procurement or finance percolating along network structures where households, firms, banks and the government interact. For example, Hallegatte (2008) provides a model of shock propagation within Louisiana after the impact of hurricane Katrina. In the model, firms adapt their behavior in an input-output network.[5]

[5] Input-output are powerful tools to assess how a shock on one or several sectors propagates into the economy through intermediate consumption and demand Haimes and Jiang (2001); Okuyama (2004); Cochrane (2004).

The model has also been employed to to assess the risks of coastal floods in a climate change framework and extended to examine the role of inventories in production dynamics and supply shortages (Hallegatte et al., 2010; Hallegatte, 2014). Simulation results show that propagation mechanisms are essential for the assessment of the consequences of disasters, and that taking into account residual production capacities is necessary not to overestimate the positive economic effects of reconstruction. A straightforward consequence is the central role played by the topology of the production network, which determines how firms are linked each other and how (intermediate) goods flow though these links. Similarly, Henriet et al. (2012) disaggregate industry input-output tables to represent the production structure of regional economies at firm level. They show that aggregate damages stemming from exogenous disasters are deeply affected by the network structure and the final outcomes depend especially on network concentration and clustering.[6]

Systems' connectivity increases dramatically the complexity of studying the impact of climate events, and the impossibility to reduce the problem through simple aggregation or to impede failures at all scales calls for a re-design of how modeling climate and weather damages (see also, Helbing, 2013). Moving from a relatively restricted geographical focus to a global perspective, Bierkandt et al. (2014) introduce *Acclimate*, a model designed to evaluate the consequences of extreme climate events through the global supply chain. The model nests agent-based features (consumption and production sites are treated as agents) in an input-output network employed to track flows of goods in the system (taking also into account transportation). Acclimate is particularly well suited to study the propagation of shocks and it has been extended to better explore the differences between top-down cascades promoted by forwards linkages and demand-induced backward dynamics Wenz et al. (2014). However, as it runs at very short-time scales (from days to some week), price adjustment mechanisms are nearly absent at the current stage and technical change is overlooked.

3.3 Integrated assessment agent-based models

Despite the methodological advantages that agent-based models offer to the representation of production networks, the study of system's resilience and its reaction to different kind of shocks, there have been little efforts in employing these tools to investigate the effects of climate change on the aggregate economy.[7] To the best of our knowledge, Lamperti et al. (2016) introduces the first attempt to bridge a

[6] In particular, concentration (degree of redundancy of suppliers and clients) acts as a risk sharing feature and clustering (degree of geographically dense interactions) allows small groups of interconnected firms to positively react to shocks happening outside the community they belong to.

[7] On the contrary, Okuyama and Santos (2014) discuss and devote a special issue of *Economic Systems Research* to combine the treatment of climate-related disasters within standard input-output or computable general equilibrium models.

fully-fledged agent-based integrated assessment model with a representation of climate-economic feedbacks, which take the form of stochastic shocks hitting agents with probability and size depending on the dynamics of the global mean surface temperature. The model, called *DSK*, builds on Dosi et al. (2010, 2013) and is composed by two industries populated by heterogenous firms, a financial sector, an energy module and, a climate box grounded on Sterman et al. (2013). The model replicates a wide range of macro and micro stylized facts as well empirical regularities concerning climate change and economic dynamics (e.g. cointegration among energy consumption, GDP and GHG emissions). Given its satisfying explanatory power, the model can be employed as a laboratory to study the short (transitions) and long-run (development trajectory) effects of a wide ensemble of climate, energy, innovation, fiscal and monetary policies. The model can also be extended to account for heterogenous banks, financial markets and population growth. The latter element, often overlooked in climate-macroeconomic modeling, can play a determinant role in shaping future scenarios and it has been previously included within an agent-based model in Castesana et al. (2013).

3.4 Finance and climate risks

The financing of the transition towards a low-carbon economy has still not been accurately explored in the economic literature. Indeed, as discussed above, the vast majority of modeling efforts focuses on government's fiscal policy. Recently, the role that financial and banking systems might play in inducing "green" investments and "green" entrepreneurship has received increasing attention(Mazzucato, 2015; Campiglio, 2016). Different types of green fiscal (carbon tax, tax relief and breaks on investment in renewable energy) and targeted monetary policies (green bonds and quantitative easing) are simulated in the Eirin model (Monasterolo and Raberto, 2016), which combines system dynamics and agent-based features. The authors find that green policy measures allow to improve economic performance without creating pressures on the financial system vis-à-vis a business-as-usual scenario. In such a context, the relation between fast de-carbonization policies and financial stability is emerging as a prominent concern on the climate policy agenda. On one side the financial system can foster the transition to a green development path. On the other side, it is increasingly exposed to climate risks.

Within this setting, the structure of the relationships among financial institutions might be crucial for the stability of the whole system. Focusing on this issue from a network perspective, Battiston et al. (2016) analyze the exposure of different classes of actors in the system using a well known macro-network stress testing model (Battiston et al., 2012; Bardoscia et al., 2015). They find that the direct exposure to fossil fuel and energy-intensive sectors, while limited overall, is relevant for investment funds, which in turns are highly connected with the banking system. Further, the housing sector can potentially trigger shocks which can be amplified by the financial system. Given the empirically well-documented degree of interdependences between actors in the financial, production and energy sides of the economy (Buldyrev et al., 2010; Beale et al., 2011; Battiston et al., 2012; Homer-Dixon et al., 2015), the role of such relationships with respect to climate policy and their response to a changing climate, is likely to be a challenge for future macro-oriented agent-based and network models.

3.5 Open issues

Our understanding of the aggregate effects produced by climate change on the economic system is still limited. Complexity theory pushes forward the idea that single components are linked, interacting and heterogeneous. As a by-product, aggregate effects emerge from the evolution of micro behaviours.

From a macroeconomic perspective, there are three main issues that the future developments of agent-based and network models should account for. The first concerns inequality and the distributional effects of climate change. While standard models (e.g. DSGE rooted on the representative agent paradigm) require ad-hoc assumptions to deal with heterogeneity and typically confine it to a single side of the economy (Bosetti and Maffezzoli, 2013; Dennig et al., 2015), agent-based models provide a "natural" framework to answer questions like *what are the income classes that will be more adversely affected by climate change? Does inequality affect system resilience to climate change?*. However, to provide adequate answer, models rooted in complexity theory need to better account for social welfare and policy evaluation.

The second issue concerns the relationships between financial and interbank markets and the transition to a low carbon economy. While transitions are usually modeled from the real side, i.e. as self-financing structural process driven by technical change (see also section 5), better understanding the role of finance and its interrelations with innovation is the challenge ahead.

The third issue we is intimately linked to both the second and the first. While most general equilibrium models find a smooth, optimal growth path for our economy, agent-based ones endogenously generate crises, fluctuations and growth instability. Relevant questions for future research concern the investigation of what kind of climate and weather events mostly affect system's stability and how financial markets might deal with associated climate and climate-policy risks.

4 Energy markets

As the the energy sector is the main producer of CO_2 emissions (cf. Figure 1), it has a pivotal role in the transition to a low-carbon economy.

Prior to deregulation, the dispatch program was solved through optimization methods by regulated or State-owned vertically integrated utilities, whose goal was to minimize the system-wide cost of electricity generation and transmission. The adequacy of optimization models in depicting how electricity markets work has declined after the deregulation of energy markets, a process that has unfolded in many countries in the last 20 years (see e.g. Borenstein et al., 2000 or Jamasb and Pollitt, 2005). With the intended consequence of lower electricity prices for end users, competition has been introduced in a market characterized by technological entry barriers. Oligopoly models assuming optimizing producers have been crafted to analyse the new scenario (see Ventosa et al., 2005), yet they often neglect the complexity of setting bids and offers for power on a physical network subject to load balancing constraints and spatial externalities. Cognitive biases of market participants cannot be neglected, either (see Rothkopf, 1999; Denton et al., 2001; Rassenti et al., 2003).

Electricity markets are thus perfect candidates for the application of computational methods, see e.g. Tesfatsion (2003), Sun and Tesfatsion (2007), or overviews in Weidlich and Veit (2008) and Guerci et al. (2010). ABMs have entered the policy-making process as decision-support tools (e.g., Nicolaisen et al., 2001, Guerci et al., 2005 and Li and Tesfatsion, 2009). Through ABMs, scholars have explored issues such as pricing rules and market power exercise (Bower and Bunn, 2001, Bunn and Oliveira, 2003, Bunn and Martoccia, 2005, Guerci et al., 2008, Kowalska-Pyzalska et al., 2014) and, closer to our interests, the comparative effects of climate policies on the diffusion of renewables and on energy efficiency, that in turn affect electricity prices. Few works have compared the explanatory power of optimizing models and ABMs with respect to electricity market dynamics, concluding in favor of ABMs (see Saguan et al., 2006 and Guerci and Sapio, 2011).[8]

4.1 Support to renewables and its effects

The influence of climate policy on electricity markets can work through several channels. Climate policy can stimulate the diffusion of energy efficiency and renewable energy technologies, which in turn impact upon the properties of electricity price series by changing the shape and dynamics of electricity demand and supply. The pattern of effects closely depends on the policy mix that has been implemented.

The integration in the existing transmission and distribution networks of a large number of micro-generators, characterized by unpredictable generation profiles, represents an important challenge for transmission system operators (Bruckner et al., 2005, Anaya and Pollitt, 2015 in the special issue edited by Boffa and Sapio, 2015), given that the existing grids were conceived under the so-called centralized generation paradigm (Kunneke, 2008). In a recent attempt to study a 100% renewable scenario in the Australian market, Elliston et al. (2012) try to match the actual hourly electricity demand of five

[8] Applications of the ABM methodology to other energy markets are less frequent, e.g. Voudouris et al. (2011) on crude oil markets.

selected states and one territory of Australia. The 100% renewable supply scenario is shown to be technically feasible, but the challenge is to cover winter evenings in the days when the sun-powered supply is low, i.e. overcast days, and wind speed is too low. Biomass fueled gas turbines coupled with the efforts to increase the winter peak demand are necessary to solve this issue. The need to rely on gas fueled micro-generation is consistent with the results in Faber et al. (2010), whose ABM indicates that gas prices, as primary fuel of this technology, are a critical component in the success of the decentralized paradigm.

Is the cost of large renewable penetration rates worth it? In the short run, lower electricity prices ensue because fossil fuel sources, characterized by relatively high marginal costs, are displaced (the so-called merit order effect). de Miera et al. (2008) simulated the power market solution based on Spanish data, to find that the merit order effect was stronger than the cost of renewable energy support arising from feed-in-tariffs. In Banal-Estanol and Ruperez Micola (2011), the merit order effect is not enough to lead to competitive pricing. This is the outcome of a simulation model in which two symmetric high-cost plants compete with a low-cost wind power plant. Intermittency in wind power generation gives rise to uncertainty on the market-clearing solution, which is hedged by generating companies by means of positive price-cost margins. In the above cited works, power plant capacities were given. Browne et al. (2015) explore the merit order effect in a model wherein capacity investments are instead endogenized. In such a long-term scenario, simulations show that the merit order effect is counteracted by market power exercise, which is also causing an inefficient electricity dispatch.

One reason behind the persistence of market power in the long-run concerns the network configurations arising in an increasingly decarbonized electricity industry. Along these lines, Guerci and Sapio (2012) investigate the impact of increasing wind power capacity on the Italian wholesale electricity prices and on power grid configurations. The simulation outputs show that electricity prices decrease in response to increasing wind power generation, but remain above marginal costs due to the increasing frequency of grid congestion, calling for investments in transmission infrastructures. The simulations in L'Abbate et al. (2014) aimed to assess the prospective effects of interconnections between Northern Africa and Italy, which could exploit the immensely rich potential of the Sahara desert for solar thermal power production, as envisaged by the Mediterranean Solar Plan (see also Sapio, 2014 and the book by Cambini and Rubino, 2014 on this issue). The authors found that Italy would become a net importer of renewables from Africa, leading to electricity price reduction. The endogenous adaptation of grid infrastructures, though, is missing from both models.

Taking steps forward from the above literature, Mureddu et al. (2015) develop an hybrid agent based and network model, which uses grid topology as an input and simulates the behaviour of heterogeneous plants. The model allows to forecast the energy price and to disentangle the contribution of each primary energy source to the downward and upward electricity balancing markets. As a significant result, the authors show that market shares in the balancing market do not depend only on energy costs but stem from the a blend of dynamic response, energy costs, geographical position (which constitute the network element of the model) and interactions among the different energy sources.

4.2 Energy efficiency

A simulation study of the impact of climate policies on households energy use is performed via a domestic stock agent-based model by Lee et al. (2014), focusing on the UK. They investigate multiple scenarios (e.g. taxes, subsidies, and decarbonisation) for the evaluation of domestic energy efficiency policies. Simulation results show that the current goals (80% reduction of energy consumption by 2050) will not be completely achieved. In the most favourable scenario, a 60% reduction may be achieved from 2008 to 2050. The study briefly analyses another policy, namely the introduction of a carbon tax, that has a significant impact in the energy demand reduction in a long-term horizon, but with many political obstacles such as the risk of fuel poverty (i.e. households spend more than 10% of their income for heating and hot water) and the increase of electricity prices. The ABM in Jackson (2010) rather highlights the benefits of coordinating energy efficiency and smart grid policies, by showing through simulations that peak hour electricity demand can be reduced by one third when energy efficiency and smart grids policies are considered together.

4.3 Carbon trading and green certificates

Most literature on climate policy frames the discussion on how to achieve the emission reduction targets through market-based tools, such as carbon trading. For recent overview of the current carbon trading schemes, the reader is referred to Perdan and Azapagic (2011) and Sorrell and Sijm (2003).[9]

In Wang et al. (2012), energy generating companies are modeled as adaptive agents that are bidding in an electricity market with cap-and-trade emission systems in place. Q-learning is used to model the process of strategy updating by agents trading on different time horizons (year, week, dynamic). The results show that generating companies can receive higher profits through higher frequency of trading, raising questions on the adequate market micro-structure for emission trading with respect to the ultimate policy objective. Such an intuition is further strengthened by Zhang et al. (2011), where an ABM is used to model the Chinese market for emissions, highlighting that transaction costs can decrease total emission trading amount and market efficiency remarkably.

[9] An investigation of personal carbon trading as a future evolution of emission trading policies is discussed by Fawcett (2010).

Recently, the ABM developed by Zhang et al. (2016) shows that an emissions trading system influences obsolete power generating technologies with lower abatement levels, but does not promote the adoption of the most advanced technology. Furthermore, national emissions trading encourages power plants to adopt technologies with relatively higher removal rates compared with separate regional emissions trading systems, but a national program also decreases the adoption of the most advanced technologies. Bunn and Munoz (2016), instead, have focused on the comparative role of targeting capacity versus energy markets. Their simulations show that the replacement of coal with wind imposes extra costs related to reserve capacity, and have compared alternative policies to face this challenge, namely capacity payments funded by customers and a reliability requirement on wind generators with capital cost or energy feed-in subsidies. They find that support through capital grants is more cost-effective than through green certificates.

4.4 Open issues

Few attempts have been made to analyze the interlinkages between different markets or, more generally, to embed the energy sector in the broader economic and financial landscape. Recent insights on the network structure behind the European emission trading system (EU-ETS, see Karpf et al., 2016) suggest that the shape of the network structure itself is an important issue, possibly shedding light on the increasing financialisation of the energy sector and its long-term effects under different climate scenarios. Relatedly, as far as the authors know, the interconnectedness of producers with their parent companies and the underlying systemic risks within energy markets has not received an in-depth exploration, as it has been done for financial markets (for example see the DebtRank measure in Battiston et al., 2012). The financial interdependence of electricity markets players represents a promising field for further study. Similarly for the dynamics of mergers and acquisitions between energy companies reacting to merit order effects. Finally, while the effects of climate policies on energy markets have long been under scrutiny, not enough is known about the direct effects of climate change on energy use and on the availability of renewable energy sources.

5 Eco-innovation and climate-friendly technology diffusion

There is a growing academic interest in eco-innovation,[10] defined, rather broadly, as "the creation or implementation of new, or significantly improved, products, processes, marketing methods, organizational structures, and institutional arrangements which lead to environmental improvements compared

[10] Also known as green innovation, environmental innovation, environmentally-friendly innovation, or sustainable innovation.

to relevant alternatives" (Kemp, 2010). By fostering eco-innovation, society and policy makers can tackle a number of pressing problems, such as the depletion of natural resources,[11] security of energy supply in countries depending on fossil fuel imports, and climate change due to greenhouse gas emissions. However, innovation is not a sufficient condition for adaptation to and mitigation of climate change: it is ineffective without diffusion and adoption. By technology diffusion one means, following Rogers (1983), "the process by which an innovation is communicated through certain channels over time among the members of a social system".

Climate-friendly technologies are characterized by several specificities, which need to be taken into account in any robust approach to modelling diffusion of green innovation (Allan et al., 2014). First, one needs to consider that no single technology can stop global warming, unless one believes in climate engineering (Keith, 2013). Second, both climate change and technical change are highly cumulative processes. The full benefits of technology diffusion for the climate are only attained with a delay of several years, which also complicates policy assessments. Third, diffusion of climate-friendly technologies typically occurs in industries organized as large technical systems (e.g. the electricity industry, see Künneke et al., 2010; Markard et al., 2012), and this renders the diffusion of new technologies a highly unstable, inertial, and path dependent process.[12] Recent evidence on the diffusion of environmentally-friendly technologies can be found in Narbel (2013).

In standard, neoclassical economics, knowledge is nearly synonymous to codifiable information and assumed to almost immediately spread within the economy as well as across economies. This probably explains why, after acknowledging that diffusion has received little attention in the literature on green technology, Pizer and Popp (2008) conclude that simplistic representations that ignore diffusion may be sufficient, since most innovations exert their main impact within a decade. The issue of diffusion has not been neglected in empirical works (also by Popp himself, see Popp et al., 2011) and neoclassical models are able to reproduce the empirically observed S-shape of technological diffusion paths, but fundamental issues such as the role of uncertainty, or the role of agents' heterogeneity and the structures of interaction networks are not adequately taken into account.[13]

[11] See the literature spawned by *The Limits to Growth* (Meadows et al., 1972), as summarized e.g. by Turner (2008) and Dosi and Grazzi (2009).

[12] The history of new technology diffusion in the electricity industry is enlightening in this respect. The diffusion of nuclear power, highly compatible with existing technologies, due to similar plant size and incorporating existing turbines, was relatively fast, as it would have been the diffusion of combined-cycle gas turbines, if not hampered by oil crises in the 1970s. On the contrary, wind power is based on new technical principles and equipment, and has little compatibility with the existing infrastructure, as the output of wind farms in hardly predictable. Hence, it finds a formidable barrier to its diffusion.

[13] The workhorses of technology diffusion in the neoclassical camp are the "probit models" (Geroski, 2000), and the "epidemic models" (Kiesling et al., 2012; Bass, 1969).

In what follows, we briefly survey ABMs of diffusion in climate economics, by classifying them according to the issues they have addressed.

5.1 Behavioral heterogeneity and income inequality

In ABMs, optimizing behavior is assumed away, or it is only one of the possible behavioral patterns. In a number of works (e.g. Sopha et al. (2011), van Duinen et al. (2015), and Janssen and Jager (2001) before them) agents alternatively engage in repetition, if their income satisfaction (the ratio between actual income and potential income) is high and income uncertainty is low; in social comparison if changes in the surrounding environment cause the satisfaction level to drop and uncertainty to grow; in imitative behaviors if satisfied and uncertain; in deliberation (i.e. optimization) if their income levels are below the satisfaction threshold, but uncertainty is perceived to be mild.

Adoption decisions by optimizing agents and heuristic followers are different, as the latter's behavior is more inertial, implying longer adoption lags. If they, moreover, engage in social comparison or imitation, such inertia is magnified by their neighbor's inertia. This makes a strong case for public policy to encourage green technology adoption. The above are some implications of the ABM crafted by van Duinen et al. (2015), exploring the adoption of new irrigation technologies by agricultural producers in the face of increasing drought risk. In that model, the perceived satisfaction and uncertainty depend on climate change effects, hence producer behaviors (repetition, social comparison, imitation, deliberation) are endogenous. Climate uncertainty is found to be an additional influence slowing down adoption, regardless of behavioral assumptions.

Adoption paths, though, are affected by the very heterogeneity in individual behaviors and preferences, as shown in the ABMs of Windrum et al. (2009), Janssen and Jager (2002), and Schwoon (2006). Higher heterogeneity, indeed, can magnify the influence of some sub-sets of agents, accelerating regime transitions or, alternatively, locking the system in the existing state. In particular, Windrum et al. (2009) study how heterogeneous consumers preferences affect the incentives of firms to explore technological paradigms characterized by different levels of eco-friendliness. In their model, firms innovate by searching in a fully modular NK technological landscape (see Frenken et al., 1999), and the landscape fitness is inversely related to environmental pollution. Consumers have hedonic preferences and are heterogeneous in the importance they give to environmental quality or to other attributes of the good. They can also change their preferences, and in particular imitate those of consumers in classes having better fitness. The paper shows that higher dispersion of preferences for environmental quality lowers global pollution. This is because more dispersion implies a higher fraction of consumers who are heavily concerned with climate issues. These "eco-warriors" provide firms with the incentives to explore the technological landscape towards goods with a better environmental content, further triggering imitation of consumers from other preferences classes.

The nexus between green technology diffusion and behavioral heterogeneity can be better grasped by considering the multi-dimensional features of green eco-friendly products. Sopha et al. (2011) focus on the role of policies to foster the diffusion of new heating technologies, inspired by the case of subsidies to heat pumps and wood-pellet heating in Norway, which were beneficial only to the diffusion of the former. The model features households, who are placed on a social network and randomly follow repetition, imitation, deliberation, or social comparison behaviors. The simulations show that policies improving one attribute of the good at a time are not enough to foster diffusion. Complementarity among attributes constrains the efficacy of the diffusion policies.

Agent heterogeneity can in fact hamper diffusion if it implies that the distance between pioneer consumers and the remaining population is too high. Income inequality, in particular, can create a gap that is difficult to bridge, unless appropriate policies are designed, perhaps even in the macroeconomic domain. This is the take home message from Vona and Patriarca (2011), who assess the effects of environmental taxation and income inequality on the diffusion of energy efficiency technologies. In the model, a fall in the relative price of the green good stimulates adoption, which in turn feeds back into further price decrease via learning. An environmental tax can foster the above dynamics, as it affects the relative price of green goods. The effects of the tax are moderated by the average income level, by income inequality, and by the rate of technological learning. The paper shows that, in a high income country with sufficiently fast learning, income inequality slows down the diffusion of the green technology, because of the mentioned gap between pioneers and the other potential adopters. Reforms that aim to achieve a more equal income distribution can also improve the effectiveness of carbon taxes in stimulating the diffusion of green technologies.

5.2 Learning and information spread

One of the key parameters in Vona and Patriarca (2011) was the learning rate. A debated issue in climate policy concerns the adequacy of the phase-out period for subsidies as compared to the learning rate that an unsubsidized industry would attain (e.g. the grid parity debate on renewable energy). Subsidies to technologies that are able to "stand on their own legs" would be wasteful. Cantono and Silverberg (2009) tackle this issue by modeling an economy populated by consumers who are heterogeneous in their willingness to pay for green goods and in their social network positions. Consumers receive information on a new green technology from their neighbors. As the number of adopters grows, the price of the new green good declines, fostering further adoption. The model is simulated under various scenarios, with and without a short-term subsidy, and tinkering with the subsidy phase-out period. Simulations show that subsidies are effective if the phase-out parameter is higher than a threshold. Moreover, both very slow and very fast learning may neutralize the subsidy effects - either because it takes too much to attain the critical diffusion level, or because technology would be adopted even without subsidies.

For consumer learning to be triggered, information on the new technologies is essential. Information spread policies, though, seem to deliver their effects only under certain conditions. One of the implications from Sopha et al. (2011) is that policies based on moral suasion (e.g. through education) are ineffective. Eco-labeling is examined by Bleda and Valente (2009), who compare how two implementations of this policy (binary eco-labels, graded eco-labels) impact on green technology diffusion. Consumers scan the market in search of the highest quality product. Yet, quality is a bi-dimensional concept in the model: it concerns user quality as well as environmental quality. Consumers discard products with quality below a given threshold and choose randomly among the remaining products. Environmental quality can only be inferred through eco-labels. Firms invest cumulated profits in R&D in response to technology diffusion patterns, under the assumption that user and environmental quality are negatively correlated. Three scenarios are compared: without eco-labeling, with binary eco-labels, and with graded eco-labels. Simulation results show that an upward trend in environmental quality is only achieved with graded eco-labels.

5.3 Open issues

The reviewed ABMs fully take account of agent heterogeneity and direct non-price interactions, but ABMs could fruitfully meet the *systems approach challenge* by Soete and Arundel (1993), according to whom the speed of diffusion of a new technology depends not only on the market for the innovation itself, but also on markets for related technologies, on the internal structure of the adopting firms (including the flexibility of its organization), and on its current knowledge base and capability to learn. To our knowledge, ABMs of green technology diffusion have not addressed this challenge yet. As an instance of this, no attention has been paid so far to the firm-level strategies employed to reduce emissions, and in particular to the choice between "end-of-pipe" clean-up technologies and "process redesign" (see e.g. the discussion in Allan et al., 2014).[14] Secondly, ABMs still do not capture some

[14] End-of-pipe technologies are the traditional target of environmental regulation and reduce emissions and/or mitigate their adverse impacts by treating an effluent stream and either neutralising the emissions or redirecting them to less harmful disposals. In contrast, pollution prevention can be enacted by means of a re-design of production processes. However, whereas end-of-pipe pollution control entails explicit and large capital outlays, related to the installation of new equipment, the costs of process re-design are more subtle and hard to calculate, which then poses several hurdles to the

other important specificities of climate-friendly technologies, such as the global nature of the climate externalities. Concerning policy assessments, it is worth noting that it is unclear from the existing ABMs whether diffusion benefits more from market-based policies or from command-and-control ones. ABMs have so far mainly focused on how single policies affect the introduction and diffusion of climate-friendly technologies. An extensive policy exploration approach would, instead, assess the effect of policy portfolios and of varying the weights of the various policies in the portfolio.

6 Conclusions

The consequences of climate change for human welfare are likely to be enormous, and the intellectual challenges presented by the economics of climate change are daunting. Complex systems science offers flexible tools to analyse the relationship between the physical and the socio-economic system. By accounting for heterogeneous agents and their interactions, agent based and network models allow one to isolate mechanisms and effects that would otherwise be missing in the picture. This explains why these models have recently been put forward as prominent alternatives to standard models rooted in the general equilibrium paradigm (Farmer et al., 2015; Stern, 2016; Mercure et al., 2016).

In this paper, we reviewed the existing literature on complex system approaches to climate-related issues. We identified four major areas of contribution and, for each of them, we discussed the open challenges. The surveyed fields encompass climate negotiations and the formation of coalitions, macroeconomic and financial aspects linked to climate change, which comprehend (but are not limited to) integrated assessment, energy sector dynamics, and the innovation in climate-friendly technologies and their diffusion.

Various challenges remain to be undertaken and climate economics might benefit from a more extensive use of agent-based and network approaches. In particular, the relationship between inequality and climate damages and the effects of agents' interconnectivity on climate policies and on the systemic stability of production and financial networks are amongst the major issues that complexity theory models of climate change are starting to investigate, and that would be extremely difficult to analyse relying on any other framework.

At the same time, as the adoption of agent-based and network models to study the economics of climate change is quite recent, there are still high margins of improvements and issues to be addressed. In particular, the next generation of ABMs should try to bridge the different research areas discussed in this survey. Fully-fledged integrated-assessment agent-based model should provide a more detailed description of energy markets, "green" technological innovation and diffusion along the lines of the micro

diffusion of more eco-friendly production processes.

and meso models presented in Sections 4 and 5. Similarly, climate coalition formation and negotiations should be studied in macro ABMs. Finally, both micro and macro ABM should provide a better account of the interrelations between financial markets, the real economy and climate change. How can financial markets promote or hinder the discovery and diffusion of eco-friendly technologies? What is the impact of stranded assets on energy production and more generally on macroeconomic dynamics? Can new financial institutions (e.g. development banks, see Mazzucato, 2015) and unconventional policy measures (e.g. "green" quantitative easing) foster the transition to a low-carbon economy? These are some of the questions that network and agent-based models should answer in the next years.

Acknowledgments

The authors would like to acknowledge financial support from different European Projects. Francesco Lamperti, Antoine Mandel, Mauro Napoletano, Andrea Roventini and Alessandro Sapio acknowledge financial support from European Union 7^{th} FP grant agreement No. 603416 - IMPRESSIONS. Tomas Balint and Antoine Mandel acknowledge financial support from European Union 7^{th} FP grant agreement No. 610704 - SIMPOL. Antoine Mandel, Mauro Napoletano and Andrea Roventini acknowledge financial support from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 640772 - DOLFINS and No. 649186 - ISIGrowth. All the usual disclaimers apply.

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Towards Agent-Based Integrated Assessment Models: Examples, Challenges and Future Developments

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September 14, 2016

Abstract

The increasing likelihood of exceeding the 2 degree target calls for a cautious analysis of the socio-ecological system functioning under high-end scenarios. Understanding the complex, dynamic and non-linear relationships between human activities, the environment and the evolution of the climate is pivotal for policy design and requires appropriate tools. Despite the existence of different attempts to link the economy (or parts of it) to the evolution of the climate, results have often been disappointing and criticized. In this paper we discuss the use of agent-based modeling for climate policy integrated assessment. First, we identify the main limitations of standard models and stress how framing the problem from a complex system perspective might help overcome them, in particular when extreme climate conditions are at stake. Second, we present two agent based models that serve as prototypes for the analysis of coupled climate, energy and macroeconomic dynamics. Finally, we provide a careful discussion on testable policy exercises, modeling limitations and open challenges for this stream of research.

Keywords: climate change, climate policy, integrated assessment, transitions, agent-based models.
JEL: C63, Q40, Q50, Q54.

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Contents

1 Introduction

Climate change is amongst the major challenges mankind has ever faced. To deal with it, policy makers need support and guide from reliable information about the co-evolution of the ecological and socio-economic systems. While climate scientists have made enormous progress in understanding the physical mechanisms involved in climate change, there is a lively debate on the usefulness of existing economic models for the analysis of how rising temperature and more frequent and catastrophic weather events might impact the economy and, more general, the whole society.

The existing Integrated Assessment models (IAM), which are widely employed by the Intergovernmental Panel on Climate Change (IPCC) to estimate the socio-economic losses of climate change and more generally the social cost of carbon (SCC, see e.g. IPCC, 2014), are fiercely criticized by an increasing number of scholars (see Pindyck, 2013; Stern, 2013, 2016; Weitzman, 2013; Revesz et al., 2014; Farmer et al., 2015; Balint et al., 2016, among many contributions). In a nutshell, IAMs provide a completely ad-hoc representation of the relationship between CO_2 atmospheric concentration and temperature increases, as well as of the damage function linking climate change to socio-economic damages (Pindyck, 2013). Indeed, they usually underestimate or neglect the scale of the scientific risks, which can possibly lead to the emergence of tipping points and non-reversibilities (Stern, 2016).

On the economic side, the assessment of the cost of climate change is performed employing a social welfare function, which again is grounded on questionable assumptions about the discount rate and does not satisfactory account for uncertainty. In particular, the IAMs ignore the possibilities of (small probability) catastrophic climate outcomes that could lead to huge expected economic damages. Moreover, IAMs are developed around the concept of market equilibrium, wherein a small number of representative firms and households maximize an expected utility or profit functions. The assumption of the representative agent is questionable on both theoretical (Kirman, 1992) and empirical (Forni and Lippi, 1997; Heckman, 2001) grounds and it prevents IAMs to study the dynamics of income and wealth inequality related to climate change and the possible policy responses. Similarly, the straitjacket of market equilibrium does not allow to study the effects of Schumpeterian technical change, which could lead to the emergence of the radical and disruptive innovations necessary to support a "green" transition.

For all the aforementioned problems, IAMs tend to underestimate the cost of climate change and the benefits resulting from the transition to a low carbon-emission economy (Stern, 2016). Given the current impasse, new approaches to modeling the co-evolution of climate change and economic dynamics are needed. In the last years, agent-based, network and system-dynamics models have been increasingly advocated as possible alternatives to more standard approaches (Balbi and Giupponi, 2010;

Kelly et al., 2013). In that, agent-based models (Tesfatsion and Judd, 2006; Fagiolo and Roventini, 2012, 2016) constitute a valuable and promising approach (Smajgl et al., 2011; Farmer et al., 2015; Stern, 2016; Mercure et al., 2016; Balint et al., 2016).

Agent-based models consider the real world as a *complex evolving system* (more on this in Farmer and Foley, 2009; Rosser, 2011; Kirman, 2016 and in the introduction of Dosi, 2012) wherein the interaction of many heterogenous agents, possibly across different spatial and temporal scales, gives rise to the emergence of aggregate properties that cannot be deduced by the simple aggregation of individual ones (Flake, 1988; Tesfatsion and Judd, 2006). The development of agent-based integrated assessment model can overcome the issues plaguing IAMs and ease stakeholder participation and scenario plausibility exploration (Moss et al., 2001; Moss, 2002a). Indeed, the higher degree of realism of ABMs (Farmer and Foley, 2009; Farmer et al., 2015) allows to involve policy makers in the process of the development of the model employed for policy evaluation (Moss, 2002b).

In this paper we present a critical review of the existing literature about complex approaches to the macroeconomics of climate change, especially focusing on agent-based models (cf. Section 2). We will then present two macroeconomic agent-based models which can be employed as prototypes for the integrated analysis of climate and economic dynamics, as well as for the study of transitions towards greener production and energy systems. The *LAGOM* family of multi-agent models (Haas and Jaeger, 2005; Mandel et al., 2009; Wolf et al., 2013) is designed to represent the evolution of economic systems providing a detailed representation of production activities at the sectoral and regional levels (see Section 3). It allows to track changes in technologies that are crucial for climate change mitigation and to explore the set of the ensuing possible economic trajectories. The *Dystopian Schumpeter meeting Keynes* model (*DSK,* Lamperti et al., 2016) studies the co-evolution between a complex economy and a climate box (see Section 4). The DSK can be considered the first agent-based integrated assessment model allowing to study the impact of different micro and macro climate shocks and the effects of alternative ensemble of policies (e.g. innovation, industrial, fiscal and monetary policies) in fostering transitions toward a sustainable development path. The main results, potentialities and complementarities between the two models will be discussed in Section 5. Finally, we will consider the open issues and future developments that macroeconomic agent-based models must face in order to provide a satisfactory integrated assessment of climate change and economic dynamics (cf. Section 6).

2 Complex systems and climate-change macroeconomics: literature review

Studying the co-evolution of climate and the macroeconomy poses non-trivial challenges. First, climate change occurs on a time scale that is longer than the length of available macroeconomic time series, hence empirical explorations of the interdependencies between the two systems are difficult.[1] Second, climate damages are hard to characterize, since it requires understanding human responses to unprecedented warm climates and to extreme weather events. As we discussed in the previous section, most Integrated Assessment Models do not perform satisfactorily in that respect. These issues call for a re-design of how climate and weather damages are modeled (Helbing, 2013), taking into account that due to complexity, aggregate climate impacts cannot be reduced to the simple aggregation of microeconomic impacts.

Given the foregoing issues, one of the main advantages of macro agent-based models (ABM) is to allow for a micro-level representation of the interactions between climate change and economic dynamics (see e.g. Moss, 2002a; Farmer et al., 2015; Balint et al., 2016). Indeed, the agent-based approach can better account for the out-of-equilibrium dynamics shifting the economy from a business-as-usual scenario to a green growth path. Macroeconomic ABMs have blossomed in recent years, and with them a new generation of agent-based integrated-assessment models (Lamperti et al., 2016). In what follows, we provide a survey of the recent contributions grounded in the complex system approach to climate-change macroeconomics (see Balint et al., 2016, for a detailed survey on complexity and the economics of climate change).

The first complexity-based models employed to study climate change are perhaps System Dynamics (SD) models.[2] Such models rely on computer simulations to explore the behavior of aggregate non-linear systems characterized by different feedback loops. Much alike ABMs, SD models allowed to study out-of-equilibrium dynamics of complex systems, but unlike ABMs, in their early instances they only employed aggregate equations, without explicitly modeling agent-level decisions. Subsequently, despite accounting for feedback loops, non-smooth aggregate behaviour and multiple equilibria, microeconomic assumptions in SD models have often been in line with the standard CGE framework. One instance is given by the MADIAMS model family, a multi-actor SD-based integrated assessment model for climate policy analysis (Hasselmann, 2010), that assumes agent homogeneity and utility maximizing behavior within each module (see also Hasselmann and Kovalevsky, 2013; Kovalevsky and Hasselmann,

[1] For example, in Dell et al. (2012) temperature shocks do not seem to affect developed economies over the available sample period of 50 years.

[2] The System Dynamics simulation approach originates from the pioneering work by Forrester (1958).

2014). Fiddaman (1997) is amongst the first SD models for the integrated assessment of climate change, allowing for tipping points and non-linear dynamics within the climate system. Follow-ups assessing climate policies include Mastrandrea and Schneider (2001); Fiddaman (2002); Sterman et al. (2012, 2013); Akhtar et al. (2013); Siegel et al. (2015). The cross-fertilization between SDs and ABMs might be extremely productive as it gives the opportunity to gradually take account of heterogeneity, network structures and boundedly rational behaviors, as well as to identify how relaxing the standard assumptions impacts on the explanation of macro level phenomena (e.g. likelihood of green transition or emissions' growth rates).[3]

One of the main advantages of SD and ABMs vis-à-vis "traditional" IAMs is their capability of accounting for system connectivity. Indeed, IAMs ignore the propagation of shocks and climate damages across interconnected sectors. Moreover, as most IAMs do not allow for agent heterogeneity, they entirely overlook the distributional issues linked to climate damages. On the contrary, models grounded in the complex system approach account for the emergence of aggregate damages from micro shocks in production, procurement, or finance, percolating along network structures where households, firms, banks, and the government interact. For instance, the model developed by Hallegatte (2008) has studied the propagation of shocks in Louisiana after the impact of hurricane Katrina (see also Hallegatte et al., 2010; Hallegatte, 2014, for extensions focused on the role of inventories in the adaptation to extreme climate events). The relationship between the topology of the production network and the resilience to natural disasters has been analyzed in (Henriet et al., 2012). Moving from a relatively restricted geographical focus, Bierkandt et al. (2014) develop a model nesting agent-based features (consumption and production sites are treated as agents) in an input-output network that allows to track flows of goods in the global supply chain. The model yields a novel understanding of the propagation of shocks and of the difference between top-down cascades promoted by forward linkages and by demand-induced backward dynamics (Wenz et al., 2014).

Long-run macroeconomic dynamics is beyond the horizon of the aforementioned models, as they run at higher time frequencies in which price adjustments and technical change can be assumed away. Yet those works, while limited in scope, outline the microeconomic backbone from which a realistic macroeconomic dynamics can emerge. A seminal contribution in studying the transition of the macroeconomy towards a low-carbon growth path is Robalino and Lempert (2000) (see also Brouwers et al., 2001), who test, through an ABM, the effectiveness of incentives to technology adoption vis-à-vis carbon taxes and emissions trading. They find that coupling carbon taxes and technology incentives is the best ap-

[3]For a discussion on ABM and SD models in the context of integrated assessment see also Kelly et al. (2013) and de Vries (2010).

proach to cut greenhouse gas emissions.[4] Notwithstanding these interesting insights, the model is too simple to account for multiple equilibria and endogenous growth, which can be particularly relevant for climate policy analyses. Indeed, in the presence of multiple equilibria, the mitigation problem is not linked to scarcity but rather to a coordination issue (Jaeger, 2012). More generally, policy makers should re-frame the problem of climate change from a zero-sum game to a win-win situation, in which climate change can be mitigated while stimulating the economy (Jaeger et al., 2013). In that respect, one of the first attempts to explore coordination issues in climate policy within a complexity modeling framework can be traced back to the LAGOM model family (Haas and Jaeger, 2005; Mandel et al., 2009; Wolf et al., 2013), to be presented in details in Section 3.

Economic dynamics mainly affect climate change via the amount of GHG emissions stemming from production of goods, capital and energy. Beckenbach and Briegel (2010), for example, limit themselves to the study of a generic production process, which is decomposed across different but not well-specified sectors. Growth is triggered by firm-level innovation and imitation strategies, in Schumpeterian fashion, and emission dynamics depends on two exogenous parameters governing the diffusion of low-carbon innovations and their quality.

A step forward has been made by Gerst et al. (2013), who propose an ABM that *completely* endogenizes the diffusion of low-emission machines. Drawing on the Keynes+Schumpeter model (K+S, cf. Dosi et al., 2010), the authors study a complex economy composed of two vertically related industrial sectors and an energy production module, where competing technologies can be used to generate energy that is subsequently distributed through the system. The model is calibrated on US macroeconomic data and simulated until the end of the century to study different carbon tax recycling schemes. Only a policy focused on subsidies to carbon-free oriented R&D allows a swift transition away from "dirty" energy technologies, and, in turn, to higher economic growth (see also Rengs et al., 2015).

The contributions described so far do not consider the feedbacks that agents (firms, energy generation plants, households, etc.) receive from increasing and possibly more volatile temperatures due to climate change. Isley et al. (2013) draws on the baseline setting provided by Dosi et al. (2010) to build a hybrid agent-based IAM. The authors underline the usefulness of the approach in analyzing transformative solutions, that is, in examining how measures to reduce GHG emissions can trigger market-induced transformations which in turn affect the ability to maintain the climate policy. However, the climate system is left out of the picture and damages are linked to emissions, not to the dynamics of the average surface temperature. Moreover, environmental damages are modeled like in

[4] Such conclusions has been later obtained in a general equilibrium model by Acemoglu et al. (2012). See also Lamperti et al. (2015) where this policy mix is contrasted with a regulatory policy intervention.

standard IAMs as aggregate cuts to potential GDP levels (see e.g. Nordhaus, 1992, 2008; Tol, 1997).[5]

Despite the methodological advantages that ABMs offer to the representation of production networks, the study of system resilience and its reaction to different kind of shocks, there have been little efforts in employing these tools to investigate the effects of climate change on the aggregate economy.[6] The DSK model (Lamperti et al., 2016) presented in Section 4 is to our knowledge one of the first attempts to bridge a fully-fledged agent-based integrated assessment model with a representation of climate-economic feedbacks represented as stochastic microeconomic shocks, whose probability and magnitude depend on the dynamics of the global mean surface temperature.

The DSK and the LAGOM models, which can be employed as prototypes for the integrated analysis of climate and economic dynamics, as well as for the study of transitions towards greener production and energy systems from a macroeconomic perspective, will be described and compared in the next sections.

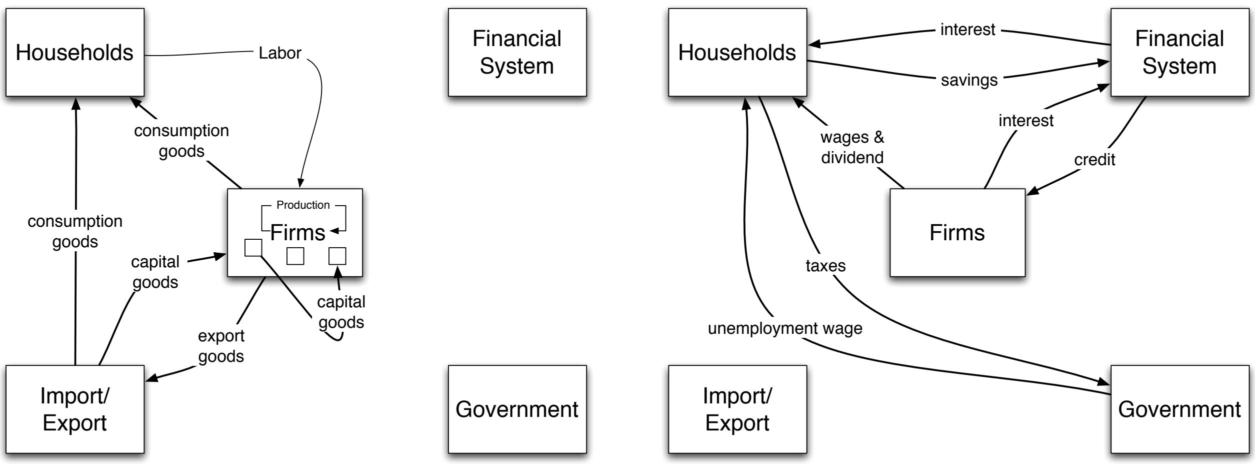
3 The LAGOM model

The objective of the LAGOM family of models (Haas and Jaeger, 2005; Mandel et al., 2009; Wolf et al., 2013) is to overcome two main shortcomings of existing IAMs based on general equilibrium (or optimal growth) models: the assumption that the economy has a single equilibrium and, correlatively, the absence of any representation of out-of-equilibrium dynamics or of the coordination process between agents. In this setting, climate policy can only induce a deviation from the "optimal" business-as-usual scenario and hence a cost to society. Considering multiple equilibria and the transition between those allows to reframe climate policy as a problem of coordination on a different equilibrium.

Implementing this alternative perspective requires the introduction of heterogeneous agents (the uniqueness of equilibrium is closely linked to the representative agent paradigm, see Sonnenschein, 1972) and the replacement of the dynamic programming approach used in general equilibrium models, which pin points the equilibrium path without exploring the phase space of the model, by an agent-

[5] Much research work remains to be done on the financing of the low-carbon transition. Different types of green fiscal (carbon tax, tax relief and breaks on investment in renewables) and targeted monetary policies (green bonds and quantitative easing) are simulated in the Eirin model (Monasterolo and Raberto, 2016), which combines SD and ABM features. The structure of the relationships among financial institutions might also be crucial for the stability of the whole system in face of climate change. Battiston et al. (2016) use a macro-network stress testing model (Battiston et al., 2012; Bardoscia et al., 2015) and find that the direct exposure to fossil fuel and energy-intensive sectors, while limited overall, is relevant for investment funds, which in turn are highly connected with the banking system.

[6] On the contrary, Okuyama and Santos (2014) discuss and devote a special issue of *Economic Systems Research* to combine the treatment of climate-related disasters within standard input-output or computable general equilibrium models.



(a) Commodity flows. (b) Financial flows.

Figure 1: Schematic representation of the LAGOM model

based approach, which lets the dynamics emerge endogenously from the micro-economic behavior of the agents. Meanwhile, LAGOM aims at providing a level of sectoral granularity comparable with this of general equilibrium IAMs in order to track technological changes induced by climate policy and, from a more technical point-of-view, to provide a mapping with input-output tables.

3.1 The model

In order to achieve these dual objectives, the model (extensively described in Mandel et al., 2009) equips the standard Arrow-Debreu general equilibrium framework with agent-based dynamics. Namely, it considers an economy with discrete periods of time, an arbitrary number of commodities and one kind of labor. The usage of commodities is not, a priori, specialized: each can potentially be used as fixed capital, as intermediary consumption or for final consumption. The economy is populated by a finite number of firms and households, a government and a financial system. The household provides labor and consume (non-durable) commodities. The firms are partitioned into sectors according to the goods they produce using heterogenous capital and labor. The government levies an income tax and provides unemployment insurance. The financial system sets the interest rate according to a Taylor rule, collects savings from households and grant credits to firms for investment.

More precisely, agents are endowed with two main types of state variables. Stocks such as goods, capital, labour, money, savings, debt. Strategies such as prices, production targets, production technologies, reservation wages, consumption habits, interest rates. These stocks and strategies evolve during a sequence of micro-economic interactions, which can be summarized as follows (see Figure 1):

1. Firms sale the goods they have produced in the preceding period to other firms (for intermediary consumption and new investment in fixed capital) and to households (for final consumption). The

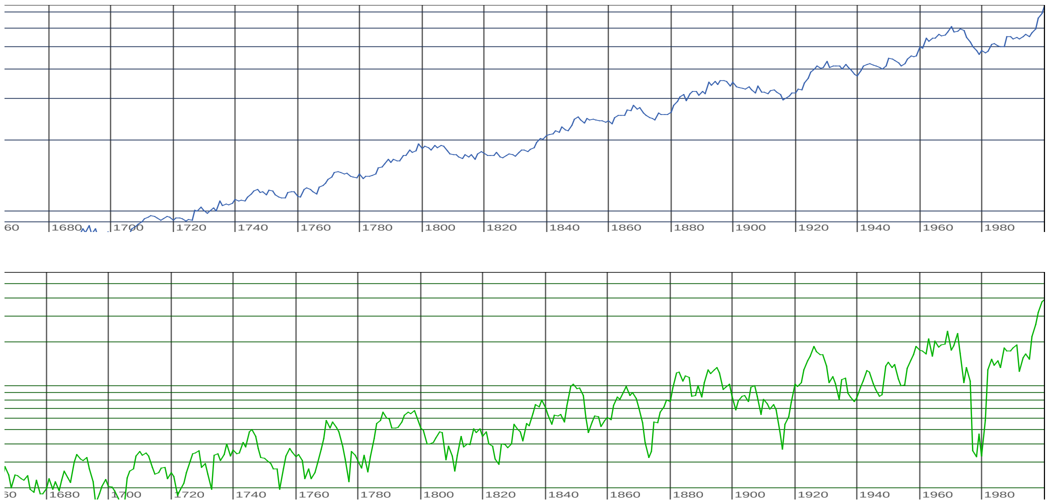


Figure 2: Evolution of output (blue) and investment (green) over 300 periods, log. scale.

trading process is organized through a random queuing mechanism as in Gintis (2006, 2007).

2. Existing labor contracts are updated as a function of the production objectives of firms and of the reservation wages of the households.

3. Firms produce goods, which are consumed by households.

4. Firms balance their accounts (possibly by borrowing money to the financial system), update their expected demand and decide on their production and price levels for the next period. Households update their expected income and decide on their consumption level for next period. The financial system updates the interest rate according to a Taylor rule.

5. Production technologies and preferences are updated according to evolutionary mechanisms, e.g some firms observe the technologies of a sample of their peers and adopt the most efficient one while some other firms explore the technology landscape at random. Moreover, the labour productivity in each sector grows as a function of net investment due to learning-by-doing.

3.2 Projections and model dynamics

The macro-economic dynamics that emerge from the micro-level interactions implemented in the model reproduce key features of empirical dynamics: exponential growth in the long-run with business cycle like fluctuations at shorter time-scales. The key macro-economic driver of these short-term fluctuations is investment, which is much more volatile than output and consumption (see Figure 2).

More generally, investment is in the model the central channel through which the micro-economic behavior of firms affects macro-economic growth. In contrast to general equilibrium IAMs where the investment decision of (representative) firms is the outcome of an optimal choice of a central planner in

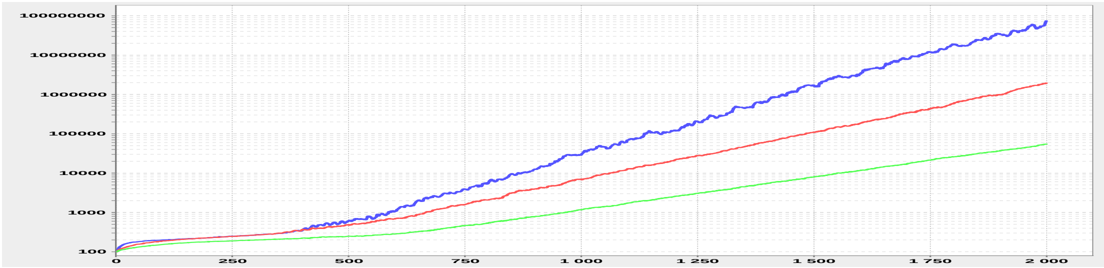


Figure 3: Output for expectations rate of change of 0.05 (green), 0.1(red), 0.2 (blue), log. scale

view of maximizing the hypothetical welfare of a representative household, in our setting, investment decisions is the outcome of firms' adaptive expectations about the profitability of new fixed capital. As in a Keynesian beauty contest, these expectations influence the actual macro-economic outcomes. Indeed, if expectations coordinate on a high growth path, investment will actually raise leading to higher demand and hence create a positive feedback loop on expectations leading to a high growth path. Conversely, a negative shock on expectations will generate a negative feedback loop. Figures 3 and 4 illustrate the strength of the induced relationship between expectations and economic growth. Figure 3 highlights how the long-term growth rate, as well as the volatility, of the economy increases when expectations are updated in a more aggressive manner by the firms. Figure 4 highlights how shifts in the growth regimes of the economy can be induced by an agressive monetary policy, which react strongly both to inflation and output gap. In the high growth regime, prices progressively raise until they trigger a large raise in the interest rates which affects negatively profit expectations and eventually lead to a coordination of expectations on low investment rates and a low growth path. In the low growth path, unemployment progressively raises until it triggers a large cut in the interest rate which boosts up profitability and eventually lead to the coordination of expectations on high investment rates and a high growth path.

The model could also be used to assess the impacts of policies that target more directly expectations or aggregate demand. In particular, in the context of climate policies, the model could be used to assess the impacts of green stimulus plans and/or large public investments in the transport or energy infrastructures. As underlined by the emphasis put on the "Juncker Investment Plan",[7] such policies are of particular concern in Europe where investments are at a record low: whereas the investment rate remained relatively stable around 25% of GDP at the global scale, it failed from 30% to 20% in the European Union in the past 40 years and conversely increased by 10% in China.[8]

Another crucial aspect of economic dynamics for climate policy is technological change and in

[7] One could argue that "The Juncker Plan" consisted mainly in influencing expectations as it assumed a 20 to 1 leverage ratio between private and public investment.

[8] See e.g http://data.worldbank.org/ for relevant data in this respect.

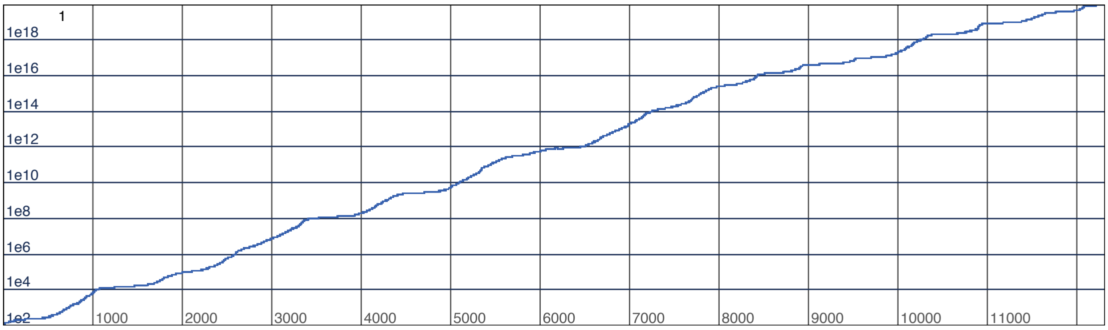


Figure 4: Long term evolution of output under a stringent monetary policy, log. scale

particular the evolution of the emission intensity of GDP. In general equilibrium IAMs, the input mix used in the reference scenario is considered as optimal, but for external effects, and hence climate policy can only induce a cost, at least in terms of productivity. In an agent-based models like LAGOM, the technological landscape evolves endogenously and the reference technology is not necessarily optimal. As illustrated in Figure 5, a wide range of technological trajectories can emerge in this setting leading to very different sectoral compositions of output. In the context of climate policy, this multiplicity of equilibria can be used to represent alternative in terms of emission intensity and analyze policies that aim to foster the transition towards a low-carbon economy.

3.3 Extension: the regional version

The model has been extended by a spatially explicit model: LAGOM regiO (see Wolf et al. (2013)), which divides the economic area under consideration into regions. The number of regions can be chosen by the model user, so that analyses at different geographical granularity are supported. Taking the Mediterranean basin as an example, one could define only two regions (North and South of the sea) as well as more detailed setting in which each country around the Mediterranean constitutes a region.

Each agent is located in a region at the initialization of the model. Agent strategies may vary across regions. While firms remain in their regions, households may migrate. Interaction and social learning processes take account of an agent's region(s) by means of adjusted probabilities of drawing the samples of observed agents. An agent obtains information about other agents belonging to the same region with a larger probability. This mechanism favors local interactions within regions over those between regions. Also, mutations of strategies occurring in a region are spread more easily within the region than across region boundaries.

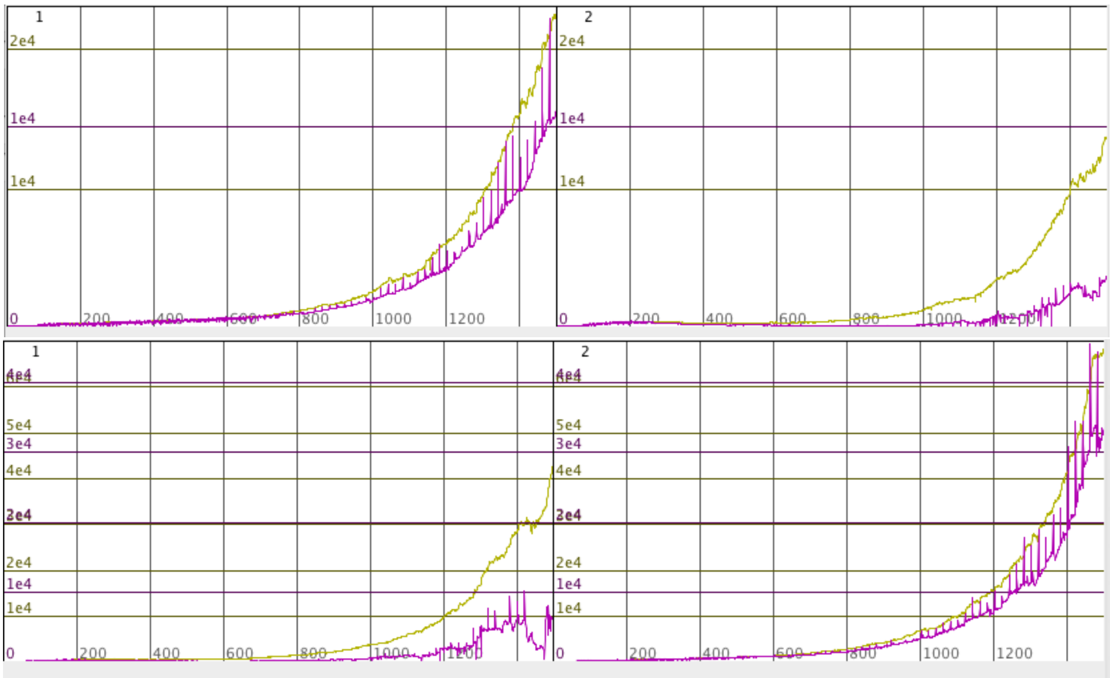


Figure 5: Evolution of output (yellow) and final consumption (magenta) in the two sectors of an economy. The top and bottom panels correspond to two different evolutions of the economy in two Monte-Carlo simulations.

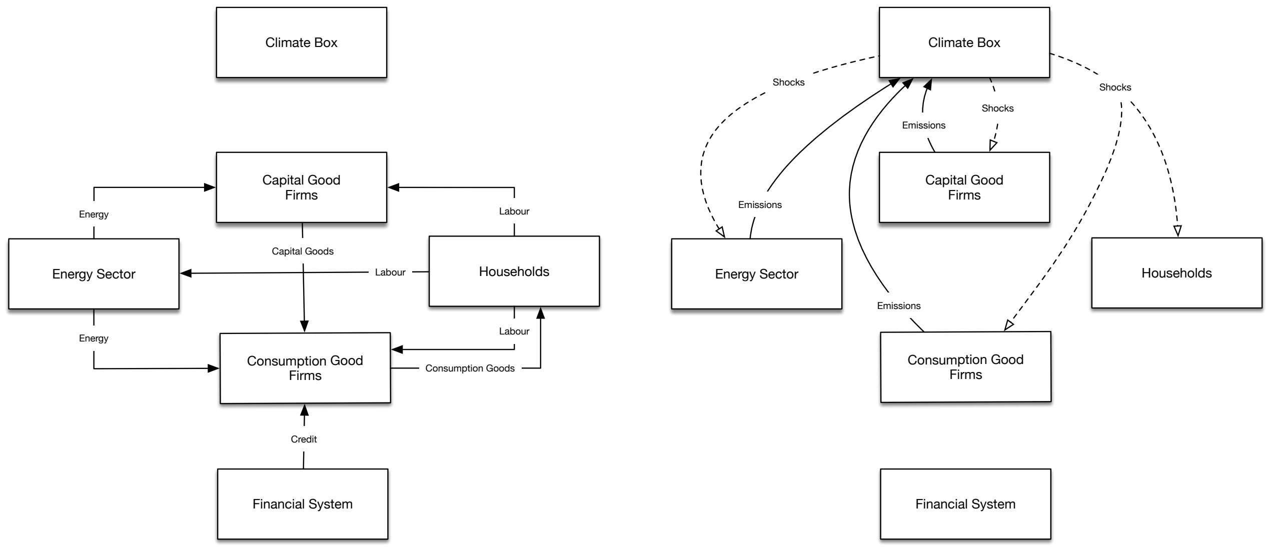
4 The DSK model

The *Dystopian Schumpeter meeting Keynes* (DSK) model captures the co-evolution between a complex economy and a climate box (more details on the model can be found in Lamperti et al., 2016). The two domains are linked via non-linear and stochastic feedbacks. As already mentioned in Section 2, the DSK can be considered as the first agent-based integrated assessment model that can be employed to provide a detailed characterization of the different micro and macro climate shocks hitting the economy. The model allows to study alternative ensemble of macroeconomic policies (e.g. innovation, industrial, fiscal and monetary policies) that can mitigate the impact of climate change, as well as sustaining the transition toward a green development path.

4.1 The model

The DSK model builds on Dosi et al. (2010, 2013) and is composed by two vertically separated industrial sectors, whose firms are fueled by an energy sector.[9] A graphical representation of the model structure is provided in Figure 6. Capital-good firms invest in R&D and innovate to improve the performances of the machines they produce in terms of productivity, energy-efficiency and environmental friendliness. Such machines are bought by consumption-good firms. Both energy and industrial sectors emit CO_2,

[9] Other contributions belonging to the so-called K+S family include Dosi et al. (2015, 2016) and Dosi et al. (2016).



(a) Economic flows.

(b) Climate-related flows.

Figure 6: Schematic representation of the DSK model.

whose concentrations in the atmosphere affect the evolution of the climate. Specifically, the carbon cycle is characterized by feedback loops in the relationship with the Earth's radiative forcing and the global mean surface temperature. The effects of an increase in the Earth's temperature on the economic system are captured by a stochastic disaster generating function. The disaster generating function changes over time according to temperature dynamics: under a warming climate, the probability of larger microeconomic shocks in labour productivity and firms' capital stock increases together with the mean size of the damage. Therefore, an increase in the Earth's surface temperature does not translate automatically in higher aggregate damages as in most IAMs; rather, it modifies at the micro level the structure of the stochastic process characterizing economic growth.

Firms in the capital-good industry produce machine tools using labour and energy. They innovate and imitate in order to increase both labour productivity and energy efficiency of the machines they sell to the consumption-good firms, as well as to reduce their own production costs. However, innovation and imitation are costly processes and firms need to invest a fraction of their past revenues in R&D activities. Technical change influences all of the three dimensions that characterize machines in our model, namely, *labour productivity*, *energy efficiency* and *environmental friendliness*.[10]

Consumption-good firms invest in machines, which are employed together with labour to produce an homogenous 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 capital

[10] Labour productivity is defined as the output per labour unit employed, energy efficiency measures the output per unit of energy and environmental friendliness captures the amount of $C0_2$ emissions for each energy unit used in the production process.

markets. Firms access firstly their net worth and if the latter does not fully cover total production and investment costs, they borrow external funds from the bank. However, firms have limited borrowing capacity: the ratio between debt and sales cannot exceed a maximum threshold depending on the firms' past sales. As a consequence, credit rationing might endogenously occur.

Energy generation is performed by a profit-seeking, vertically-integrated monopolist through heterogeneous power plants using green and dirty technologies. The energy monopolist produces and sells electricity to firms in the capital-good and consumption-good industries using a portfolio of power plants, which are heterogeneous in terms of cost structures, thermal efficiencies and environmental impact. "Green" plants convert renewable sources of energy (such as wind, sunlight, etc.) into electrical power at a null marginal production cost and produce no greenhouse gas emissions. However, large fixed costs are necessary to build up new green plants. Conversely, the stock of fossil-fueled plants can be expanded at virtually zero fixed costs, but energy generation via "dirty" power plants involves positive marginal costs reflecting either the price of fossil fuels or extraction costs. Technical change occurs along both the technological trajectories (green and dirty, see Dosi, 1988) and improve plants' efficiency and environmental friendliness.

Finally, a climate box links CO_2 emissions with atmospheric concentrations of carbon and the ensuing dynamics of the Earth's mean surface temperature. These relationships are modeled in a non-linear way through a core carbon cycle characterized by feedbacks as in Sterman et al. (2012, 2013). The climate box avoids a complex and detailed description of the physical and chemical relations governing climate's evolution, while capturing its major features, including feedbacks that might give rise to non-linear dynamics. In particular, our carbon cycle is modelled as a one-dimensional compartment box based on Goudriaan and Ketner (1984) and Oeschger et al. (1975). Atmospheric CO_2 is determined on a yearly basis by the interplay of different factors, which account for anthropogenic emissions, exchanges of carbon dioxide with the oceans and net primary production.

4.2 Projections and model dynamics

The DSK model allows to analyse two intimately linked but distinct issues:

- the long-run behaviour of the economy under global warming and increasingly large and volatile climate shocks;
- the possible transition from a carbon-intensive economy towards a greener one and the ensuing lock-in and path-dependency phenomena.

Both issues are linked to the short- and long-run dynamics of the model. The raising temperature stemming from increasing emissions can lead to stronger and more volatile climate shocks, which

Table 1: Summary statistics on selected variables under BAU and no climate damages.

	MC average	MC st. dev.		MC average	MC st. dev.
Output growth	3.19%	0.001	Share of emissions from energy sector	61.4%	0.201
Likelihood of crises	12.1%	0.076	Share of green energy	29.9%	0.285
Unemployment	12.0%	0.022	Periods green beyond 20%	33.0%	0.103
Energy demand growth	2.15%	0.002	Emissions at 2100	26.9	9.236
Emissions growth	1.19%	0.003	Temperature at 2100	4.54	0.509

Note: All values refer to a Monte Carlo of size 50. Emissions are expressed in GtC, which can be converted in $GtCO_2$ using the following conversion factor: 1 GtC = 3.67 $GtCO_2$. Temperature is expressed in Celsius degrees above the preindustrial level, which is assumed to be 14 Celsius degrees.

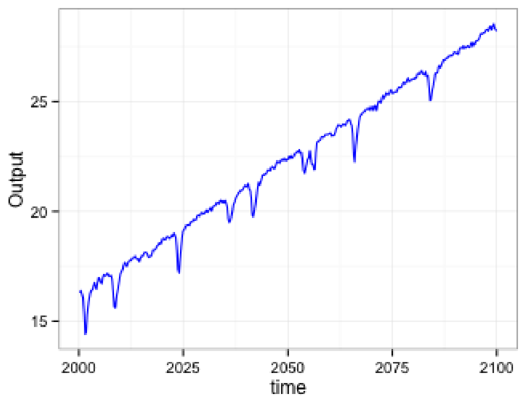
may induce downturns and crises, possibly hampering the growth performance of the economy. The transition from a dirty to a green economy can depend on business cycle conditions, but in turn can also affect potential output growth. Hence, in presence of climate change, the plea of Solow (Solow, 2005) for macroeconomic models able to jointly account short-and long-run dynamics is even more relevant.[11] The ability of the DSK model to *simultaneously* account for short- and long-run features (see Lamperti et al., 2016, for details) is, in our opinion, a key aspect of the overall exercise and a major advantage over standard IAMs.[12]

Let us now explore the dynamics of the DSK model in the benchmark, business-as-usual (BAU) scenario, where the model is calibrated and initialized on the main features of the global economy in year 2000, climate shocks are switched off and no climate policy is introduced.[13] The simulation protocol is simple: we run the model for 400 periods, which are to be interpreted as quarters, thereby obtaining projections until year 2100. The model, similarly to LAGOM (section 3), generates multiple possible trajectories, each linked to a different pattern of technical change in the industrial and energy sectors. Moreover, since the model is stochastic in its nature, we rely on Monte Carlo (MC) experiments to wash away specific patterns due to particular realizations. Figure 7 shows a representative run for three quantities of interest, while MC averages and standard deviations for the main macroeconomic and climate-related variables are collected in Table 1.

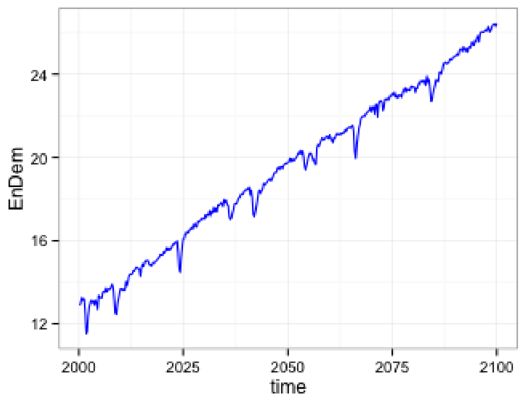
[11] On the importance of climate shocks for short-run dynamics, see Rogoff (2016).

[12] The interest reader might also want to have a look at Dosi et al. (2016), where the properties of the K+S model family, to which DSK belongs, are detailed.

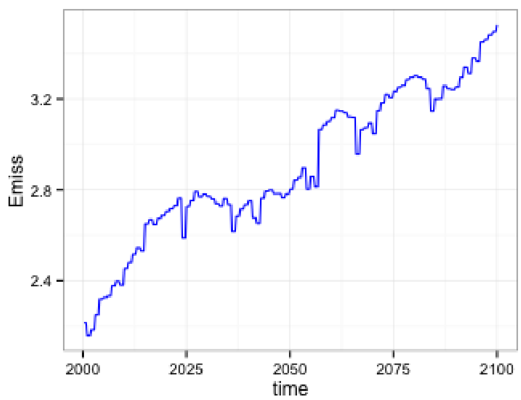
[13] In particular, the model has been calibrated through an indirect calibration exercise (Windrum et al., 2007). The model is able to track the historical evolution of the world economy with respect to a variety of measures, including output growth rates, unemployment levels, emissions growth rates and final energy consumption.



(a) Output.



(b) Energy demand.



(c) Emissions.

Figure 7: Long run evolution of selected variables, log. scale.

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 collected in Olivier et al. (2015). Unemployment rates seem to be quite stable across runs and in accordance with actual data for some countries.[14] Moreover, projections indicate that the economic system grows with endogenous fluctuations punctuated by major crises (see e.g. NBER, 2010; Claessens and Kose, 2013). Finally, simulation results show that the share of renewable energy in total energy production exhibits an average of 30% over the whole time span (2000-2010) and it is higher 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.[15]

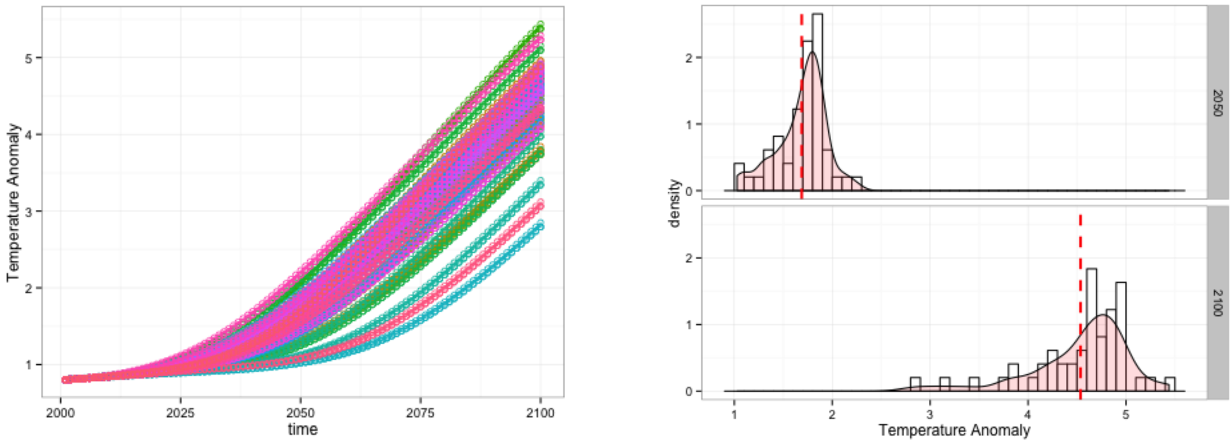
Beyond these macroeconomic features, the DSK model reproduces various micro-level stylized facts concerning industrial and energy system dynamics. Firms display persistent differentials in their productivity (in line with Bartelsman and Doms, 2000)), energy and carbon efficiency (in accordance with DeCanio and Watkins, 1998 and Petrick et al., 2013) and the distribution of growth rates exhibits fat tails (see e.g. Bottazzi and Secchi, 2006). Together with a right-skewed firm size distribution, these results point to a dis-equilibrium economic development path, characterized by persistent heterogeneity among firms.

Let us now consider the dynamics of the temperature. Figure 8 shows it along the whole time span for each of the Monte Carlo runs and reports their distribution at the middle and final point of the simulation. The results are relatively aligned with those produced by the most widely used IAMs (Nordhaus, 2014), but some remarkable differences exist. First, our average temperature projections indicate higher estimates than those in many other models (see Clarke et al., 2009; Gillingham et al., 2015), supporting a rather pessimistic view of the BAU scenario. Second, the evolution of the temperature exhibits a peculiar dynamics, which we did not observe in other contributions. In particular, a first phase of gradual increase is followed by a period (indicatively located between 2025 and 2050) when climate change accelerates dramatically, before lowering its pace and reaching a nearly constant growth in a third phase. Such a dynamics, which is driven by the feedback mechanisms characterizing the carbon cycle (see Sterman et al., 2013), call for tempestive and urgent policy interventions that must be enacted as early as possible.[16] Finally, figure 8b shows the Monte Carlo distribution of temperature at the middle (2050) and final (2100) simulation steps. Being the model stochastic only in the search

[14] See: Word Bank, WDI: `http://wdi.worldbank.org/table/2.5`.

[15] The 20% target is informative in Europe due to the so called 20-20-20 strategy.

[16] The carbon cycle feedbacks exert a relatively greater effect when the state variables in the climate box move away from the assumed pre-industrial equilibrium, while their effects becomes less important (relatively to the same change in the state variables) when climate change becomes aggressive. Given the uncertainties surrounding the behaviour of the carbon cycle under extreme conditions our modelling effort might underestimate the effects of the assumed feedbacks.



(a) Temperature projections.

(b) Distribution of temperature.

Figure 8: Temperature projections and their density estimates. Both graphs refers to a Monte Carlo of size 50. Red dashed lines in panel 8b indicate mean values.

for innovations (climate shocks are switched off), such distributions characterize the uncertainty surrounding climate change stemming from the dynamics of technical change (Dosi, 1988). Across time, the mean, the support and the tails of the temperature distribution increases, suggesting the non-linear and accelerating dynamics of climate change.

5 Discussion

The two agent-based models introduced above offer novel perspectives with respect to traditional, computable general equilibrium IAMs for the analysis of coupled climate-economic dynamics and transitions towards greener production systems. Moreover, they provide complementary tools and information sources.

First, by their very nature, they produce non-smooth growth patterns resulting from disequilibrium interactions among heterogeneous and boundedly rational agents. This contrasts with the optimal growth trajectories provided by standard models. The presence of endogenous crises is pervasive and can influence the economy's development path and the very process of climate change. For example, crises might favor the relative competitiveness of certain technologies, the final emergence of new paradigms (Perez, 2003; Kregel, 2009) and, in turn, the transition towards a greener economy.

Moreover, agent-based models provide multiple sources of information. Green transition can be studied looking at the dynamics of technology adoption at the micro level and across multiple sectors (Mercure et al., 2016). The links between firms behaviour, financing sources, consumer preferences and the aggregate performance of the economy are naturally embedded in the DSK and LAGOM models.

As already mentioned in section 2, agent-based integrated assessment models allow disaggregated climate and weather shocks and, therefore, avoid the aggregation problems faced in traditional modeling frameworks (Fankhauser et al., 1997; Anthoff and Tol, 2010).[17] Specifically, climate damages can take the form of micro level shocks to firms, consumers/workers and power plants (see Lamperti et al., 2016). Unlike standard IAMs, agent-based integrated assessment models allow to study a variety of different climate change impacts, ranging from capital destruction and productivity losses to reductions in labour force participation and workers' health. Moreover, shocks are allowed to be random events with different size. In the DSK model, for example, each agent in the system can be directly hit by a climate shock with a probability that varies according to the dynamics of temperature. Similarly, the size of the shock is dynamically affected by climate change. Indirect effects of climate shocks take place via the economic networks each agent is embedded in. This framework provides the advantage of endogenously generated catastrophic events, while leaving the modeler with larger degrees of freedom (e.g. the choice of the probability distribution from which climate shocks are sampled and the link between temperature's dynamics and the probability function). In that, Lamperti et al. (2016) propose to explore a variety of combinations of impacts and density specifications in order to build a novel set of socio-economic scenarios, each characterized by different shocks' targets, intensity of climate damages and macroeconomic performances.

While the DSK model offers a complete characterization of the feedbacks between economic activities and the evolution of the climate, the LAGOM model allows for a much more fine-grained representation of the economy as a disequilibrium production network with multiple sectors and, possibly, multiple regions. In this respect the two models are complementary: the DSK model links growth patterns to a range of possible shocks and analyses the resulting macroeconomic performance, while the LAGOM model can be used to study how such shocks propagate through the production network identifying the system resilience and crucial nodes.

Remarkably, the two agent based models allow for a wide a range of policy exercises that go beyond the mere introduction of carbon taxes. Furthermore, they allow to observe the distributional impacts of policy interventions, even within given categories of agents (see also Farmer et al., 2015). This allows to study how the couple dynamics of the economy and climate change affect inequality. Table 2 provides a non-exhaustive lists of the various policies that can be tested with LAGOM and DSK models. The flexibility of modularity of agent-based models (Fagiolo and Roventini, 2012, 2016; Balint et al., 2016)

[17] To the best of the authors' knowledge, Tol (1997) provides the only IAM allowing for sector specific climate damages, but it does not allow agent specific shocks and does not explain how sectoral damages emerge (e.g. productivity loss, efficiency loss, capital stock loss). There are also different models with regionally heterogeneous damages (Nordhaus and Yang, 1996; Bosetti et al., 2006; Anthoff and Tol, 2009), but they resort to region-specific damage or welfare functions.

Table 2: Policy exercises available in the LAGOM and DSK models.

Climate & Energy policy	**Macro policy**	**Industrial Policy**
	DSK	
Carbon tax	Fiscal Policy	Standards
Command and Control	Green Quantitative Easing	Reforms to the Patent System
Fossil Fuels Taxes	Green Bonds	
Minimum Share of Renewable Energy		
	LAGOM	
Energy Taxes and Subsidies	Labor Market Policies	
Coordination of Investments	Monetary Policy	
Expectation Management		

allow to study how different policy combinations can promote (or not) the transition to a sustainable growth pattern characterized by green production and low CO_2 emissions. Finally, the observable economic structure and climate dynamics and the higher degree of realism of the LAGOM and DSK models facilitate the interactions with policymakers and stakeholders in co-designing the policies to be tested (Moss, 2002b).

6 Open issues and future developments by way of conclusion

In this paper, we have discussed how agent-based models (ABM) represent one of the most promising approaches to the integrated assessment of climate change and economic dynamics. The goal of ABMs is to overcome the limitations of the existing Integrated Assessment Models (IAMs), which are typically nested in a representative-agent computable general equilibrium framework (e.g. simplistic representation of CO_2 concentration and temperature increases, neglect of large catastrophes, tipping points and irreversibilities in climate change dynamics, ad-hoc hypotheses concerning the shape of the social welfare function and discount rates, etc.).

Complexity-based approaches to the economics of climate change try to overcome the difficulties plaguing standard IAMs, offering a more adequate characterization of climate change dynamics and of its effects on the economy. In this paper we have outlined the main features of agent-based integrated assessment models, which characterize the economy as complex evolving system populated by heterogeneous and locally-interacting agents. In ABMs, the macroeconomic effects of climate change are modeled as emergent properties of such a dynamics and cannot be reduced to the decisions of a representative individual. Moreover, the explicit presence of a population of heterogeneous agents allows for a systematic analysis of the distributional impacts of climate change and its impact on inequality. Finally, ABMs are typically more flexible than standard IAMs, allowing for more realistic representations of damage functions, of the institutional processes shaping climate policies, and of technical change processes governing the appearance, evolution and demise of dirty and clean technologies.

We have then illustrated two examples of agent-based IAMs that have recently been developed, namely the LAGOM and DSK family of models, and we have explored their main differences and complementarities. The DSK model offers a complete characterization of the feedbacks between economic activities and the evolution of the climate. This allows for a detailed analysis of how various types of climate-change shocks affects growth paths; of what could determine the success of green transitions; and of the economic policies that can set the economy on the sustainable path. The climate-economy interplay is represented in a much lower detail in LAGOM, which however allows for a much more fine-grained representation of the multi-sectoral and spatial dynamics of the economy. Accordingly, LAGOM can be used to study how climate shocks propagate through the production network and to identify the nodes that are crucial for the resilience of the system.

Complexity-based approaches represent a promising route towards integrated assessment analyses that are better suited to grasp the essential features of the coevolution between climate and the economy (see also Farmer et al., 2015; Balint et al., 2016). Nevertheless, the understanding of the aggregate effects produced by climate change on the economic system is still limited, and there is yet a large room for their improvements. From a macroeconomic perspective, there are (at least) three main issues that future developments should account for.

The first concerns inequality and the distributional effects of climate change. While standard IAMs require *ad-hoc* assumptions to deal with heterogeneity and typically confine it to a single side of the economy (Bosetti and Maffezzoli, 2013; Dennig et al., 2015), agent-based models provide a "natural" framework to answer questions like: *what are the income classes that will be more adversely affected by climate change? Does inequality affect system resilience to climate change?*. However, to answer adequately, models rooted in complexity theory need to better account for social welfare and policy evaluation.

Second, a better understanding of the effects of finance on the transition to a low carbon economy is needed. Transitions are usually modeled as a self-financed structural process driven by technical change. This is not the case in reality, as the investment in green technologies can heavily be affected by the possibility of financing them, and thus by the decisions and incentives of financial actors to fund green investments. The study of the interplay between financial dynamics and green investment and innovation is thus one of the challenges ahead.

Finally, the major open question for integrated assessment modeling probably consists in the development and application of credible and empirically robust damage functions. In agent-based models like those described in sections 3-4, climate damages take the form of stochastic shocks sampled from time-varying distributions. Although such damage functions constitute an improvement with respect to those used in standard IAMs, they might still be considered arbitrary (see the discussion in Pindyck, 2013). The literature on disaster risk and insurance (Dilley, 2005; Li et al., 2013; Michel-Kerjan et al., 2013; Bouwer, 2013; Hallegatte, 2014) might provide empirically sound distributions for different weather and climate-change related events (e.g. capital stock loss due to a tsunami) that flexible ABMs might proxy.[18] Taking this opportunity into account would, in our opinion, help to address various critiques that damage functions usually receive.

Acknowledgments

The authors would like to acknowledge financial support from different European Projects. Francesco Lamperti, Antoine Mandel, Mauro Napoletano, Andrea Roventini and Alessandro Sapio acknowledge financial support from European Union 7^{th} FP grant agreement No. 603416 - IMPRESSIONS. Tomas Balint and Antoine Mandel acknowledge financial support from European Union 7^{th} FP grant agreement No. 610704 - SIMPOL. Antoine Mandel, Mauro Napoletano and Andrea Roventini acknowledge financial support from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 640772 - DOLFINS and No. 649186 - ISIGrowth. All the usual disclaimers apply.

[18]See also the data provided by the NASA's Socio Economic Data and Applications Center (http://sedac.ciesin.columbia.edu/theme/hazards/data/sets/browse) and by the University of South Carolina's SHELDUS initiative (http://hvri.geog.sc.edu/SHELDUS/).

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

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January 18, 2017

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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Now I am become Death, the destroyer of worlds.

J. Robert Oppenheimer

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 is 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 CO_2 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

[1]See 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).

[2]On 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).

[3]As 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.

[4]The assumption of the representative agent is questionable on both theoretical (Kirman, 1992) and empirical (Forni and Lippi, 1997;

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]

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 heterogenous 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 CO_2 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

Heckman, 2001). However, some attempts to include heterogeneity in integrated assessment models is currently under development (Bosetti and Maffezzoli, 2013).

[5] A 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 these models and Emmerling et al. (2016) for recent and detailed example.

[6] The 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).

[7] Some 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.

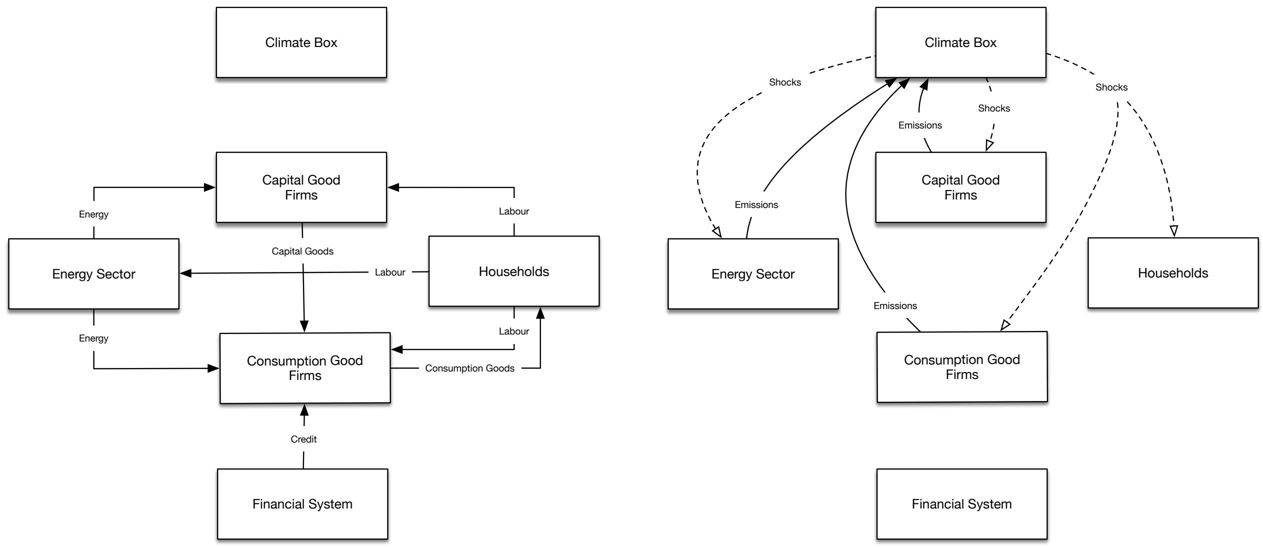
on the energy efficiency, capital stock and inventories of firms. The DSK model accounts both for frequent and mild climate shocks and low-probability but extreme climate events. Technical change occurs both in the manufacturing and energy sectors. Innovation determines the cost of energy produced by dirty and green technologies, which, in turn, affect the energy-technology production mix and the total amount of CO_2 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 heterogeneous, 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.



(a) economic flows

(b) climate flows

Figure 1: A stylized representation of the DSK model.

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 CO_2, 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 $(A^k_{i,\tau}, B^k_{i,\tau})$, with $k \in \{L, EE, EF\}$. Let us start with labor productivity, L: $A^L_{i,\tau}$ stands for the productivity of the capital-good in the consumption-good industry, while $B^L_{i,\tau}$ is the productivity of the production tecnique needed to manufacture the machine. The apex EE, instead, refers to energy efficiency: $A^{EE}_{i,\tau}$ represents the output per energy unit obtained by a consumption-good firm using the machine-tool, and $B^{EE}_{i,\tau}$ is the corresponding ratio characterizing the production of the capital-good manufactrer 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:

$$c_i^{cap}(t) = \frac{w(t)}{B^L_{i,\tau}} + \frac{c^{en}(t)}{B^{EE}_{i,\tau}}. \tag{1}$$

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

$$c_j^{con}(t) = \frac{w(t)}{A^L_{i,\tau}} + \frac{c^{en}(t)}{A^{EE}_{i,\tau}}. \tag{2}$$

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, $A^{EF}_{i,\tau}$ refers to the environmental friendliness of the machine-tool, while $A^{EF}_{i,\tau}$ 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

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

the technological advance via additional stochastic processes:

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

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

$$A^{EF}_{i,\tau+1} = A^{EF}_{i,\tau}(1-\chi^{EF}_{A,i}) \tag{5}$$

$$B^{EF}_{i,\tau+1} = B^{EF}_{i,\tau}(1-\chi^{EF}_{B,i}), \tag{6}$$

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

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

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 ac-

[9] In 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).

[10] This 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).

cording 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 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:

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

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):

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

with $0 \leq \upsilon \leq 1$.

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

[11] These 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.

[12] Notice 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.

[13] Finally, 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)

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:

$$\Pi_e(t) = p_e(t)D_e(t) - PC_e(t) - IC_e(t) - RD_e(t), \tag{10}$$

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^{τ}_{de}, where τ denotes the technology vintage. Hence, the average production cost for a dirty plant of vintage τ is given by

$$c_{de}(\tau, t) = \frac{p_f(t)}{A^{\tau}_{de}} \tag{11}$$

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^{τ}_{de} 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

[14]Furthermore, 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.

[15]The 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).

[16]The 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.

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:

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

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:

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

where $\overline{c}_{de}(\tau, t) = \max_{\tau \in IM} c_{de}(\tau, t)$. 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:

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

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

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

[18] Other 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^{τ}_{de}, the maximum production level that can be obtained with the available capacity stock is

$$\overline{Q}_e(t) = \sum_{\tau} g_{de}(\tau, t) A^{\tau}_{de} + \sum_{\tau} g_{ge}(\tau, t). \tag{15}$$

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

$$EI^d_e(t) = \begin{cases} K^d_e(t) - K_e(t) & \text{if } \overline{Q}_e(t) < D_e(t) \\ 0 & \text{if } \overline{Q}_e(t) \geq D_e(t) \end{cases}. \tag{16}$$

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, $\underline{IC}_{ge} = \min_{\tau} IC^{\tau}_{ge}$, and $\underline{c}_{de} = \min_{\tau} c^{\tau}_{de}$. If so, the producer builds $EI^d_e(t)$ units of new green capacity and the expansion investment cost amounts to

$$EC_e(t) = \underline{IC}_{ge} EI^d_e(t) \tag{17}$$

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:

$$RD_e(t) = v_e S_e(t-1) \tag{18}$$

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

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

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 $\theta_{de}(t)$:

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

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^{τ}_{ge}, is lowered by a factor $x_{ge} \in (0, 1)$ (a random draw from a Beta distribution) with respect to the previous vintage:

$$IC^{\tau}_{ge} = IC^{\tau-1}_{ge} x_{ge} \tag{20}$$

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 $(A^{\tau}_{de}, em^{\tau}_{de})$, related to the existing values as follows:

$$A^{\tau}_{de} = A^{\tau-1}_{de}(1 + x^{A}_{de}) \qquad em^{\tau}_{de} = em^{\tau-1}_{de}(1 - x^{em}_{de}) \tag{21}$$

where x^{A}_{de} and x^{em}_{de} 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 CO_2 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]

[19] In 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.

[20] Our 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).

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 CO_2 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, CO_2 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 CO_2 stock (Wullschleger et al., 1995) and it is negatively affected by temperature's increase:

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

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 CO_2 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 (Sterman 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:

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

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

[21] The fertilization feedback refers to the phenomenon of increasing biosphere's carbon uptake due to the stimulus that CO_2 atmospheric concentrations exerts on vegetation productivity (Allen, 1990; Allen and Amthor, 1995; Matthews, 2007).

[22] The 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.

[23] Our 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.

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:

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

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:

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

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:

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

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.

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

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

and surface oceans), by the CO_2 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:

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

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

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:

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

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 CO_2 concentrations, thereby modifying the biophysical equilibrium;
2. the increased carbon concentration affects oceans' marginal capacity to uptake CO_2;
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;

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

5. $C_a(t)$ affects the new radiative forcing of GHG;

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 CO_2 emissions in the atmosphere, thereby increasing its concentration. Total emissions (Em) are simply obtained by summing CO_2 emissions in the machine-tool industry (Em^{cap}), consumption-good sector (Em^{con}) and in energy production (Em^{en}):

$$Em(t) = \sum_{\tau} \left(\sum_{i} Em^{cap}_{i,\tau}(t) + \sum_{j} Em^{con}_{i,\tau}(t) + Em^{en}_{\tau}(t) \right), \tag{30}$$

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 CO_2 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.

[26] We 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.

[27] For 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.

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.).

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

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

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:

$$a(t) = a_0[1 + \log T_m(t)] \tag{32}$$

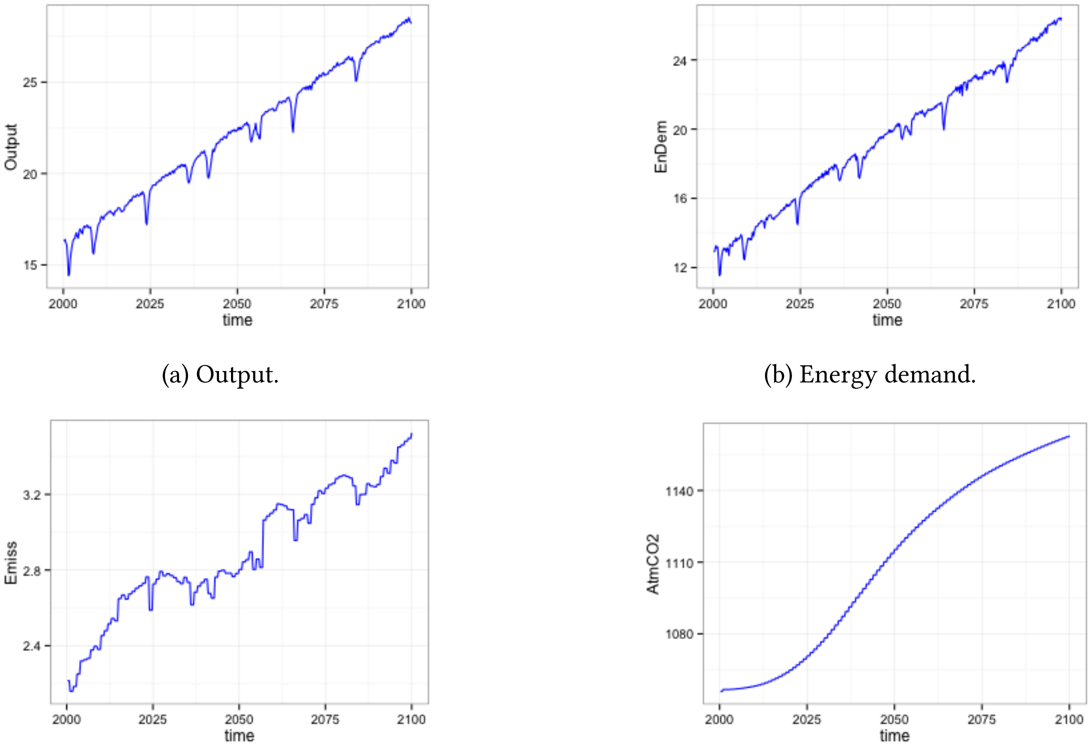
$$b(t) = b_0 \frac{\sigma_{10y}(0)}{\sigma_{10y}(t)}, \tag{33}$$

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]

[28]For 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).

[29]Naturally, 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).

[30]The 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.



(a) Output.

(b) Energy demand.

(c) Emissions.

(d) Atmospheric concentrations of CO_2.

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

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

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

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 $GtCO_2$ using the following conversion factor: 1 GtC = 3.67 $GtCO_2$. Temperature is expressed in Celsius degrees above the preindustrial level, which is assumed to be 14 Celsius degrees.

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, 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).

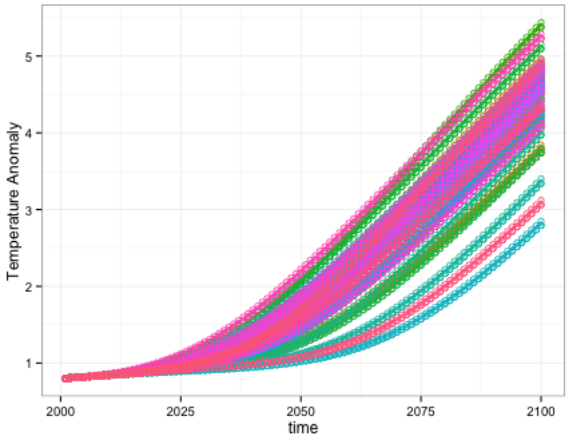
3.1 Macroeconomic and climate variable projections

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.

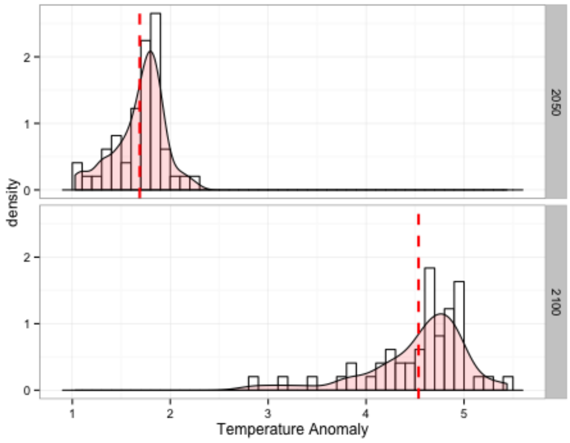
We robustly find endogenous growth of output and energy demand, which increase at relatively similar rates. Emissions steadily grow as well, but at a lower pace, in line with recent evidence (cf. Olivier et al., 2015). Moreover, projections indicate that the economic system grows with endogenous fluctuations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

[32]Extensive 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.

[33]See 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.



(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.

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.

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

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 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 are 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.

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

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 Syncronization of emissions dynamics and business cycles	Peters et al. (2012); Doda (2014)
SF11 Co-integration of output, energy demand and emissions	Triacca (2001); Ozturk (2010); Attanasio et al. (2012)
Microeconomic stylized facts	
SF12 Firm (log) size distribution is right-skewed	Dosi (2007)
SF13 Fat-tailed firm growth-rate distribution	Bottazzi and Secchi (2003, 2006)
SF14 Productivity heterogeneity across firms	Bartelsman and Doms (2000); Dosi (2007)
SF15 Persistent productivity differential across firms	Bartelsman and Doms (2000); Dosi (2007)
SF16 Lumpy investment rates at firm-level	Doms and Dunne (1998)
SF17 Persistent energy and carbon efficiency heterogeneity across firms	DeCanio and Watkins (1998); Petrick et al. (2013)

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.

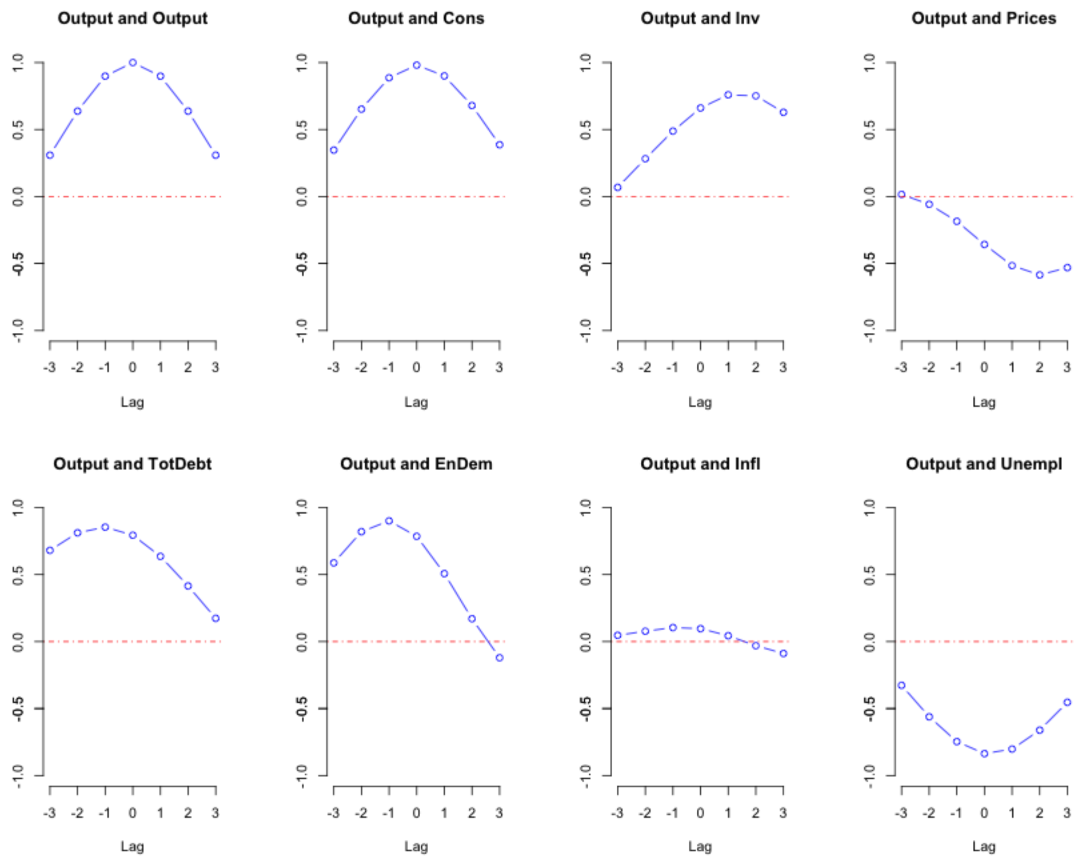


Table 3: Cointegration tests for output, energy demand and emissions. All values refer to a Monte Carlo of size 100. In the Engle-Granger procedure critical values for significance levels are taken from Banerjee et al. (1993) and there is evidence of cointegration if the test statistic is lower than 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

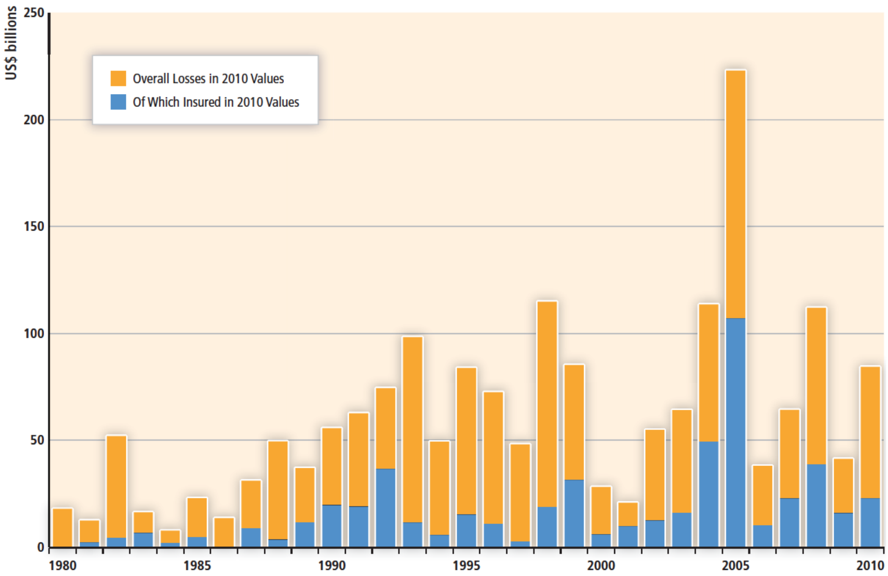


Figure 5: Climate Damages and Shocks. The figure presents monetary estimates (in 2010 USD) of climate and weather related damages. The overall losses do not include those associated to geophysical events. Source: IPCC (2013).

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 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 heterogenously 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 ($A^L_{i,\tau}$ and $B^L_{i,\tau}$) falls by a factor that varies across firms, as climate change negatively impacts on workers' operative and cognitive tasks (Seppanen et al., 2003, 2006).

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

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

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

- *Energy efficiency (EF) shocks.* Firm-level energy efficiency ($A^{EE}_{i,\tau}$ and $B^{EE}_{i,\tau}$) 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 loose part of their stock of machines, while capital-good firms loose 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 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

[36]The 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).

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.

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

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

(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.

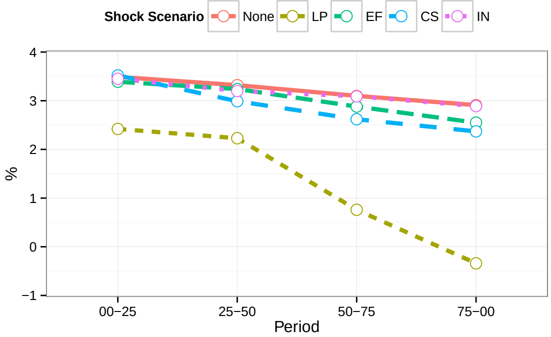
The heterogeneous impact of shocks is also linked by the highly *non-linear* dynamics of the economy. We report in Figure 6 the average MC value of output growth rate, likelihood of crises and unemployment in the different scenarios, segmenting the simulation into 4 non-overlapping windows lasting 25 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 that 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 specificallly, 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

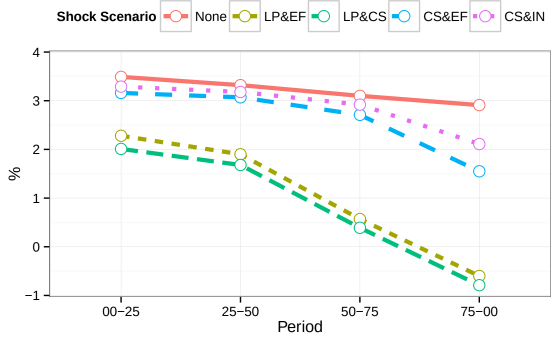
[37] Further scenarios, obtained by means of further combinations of shock targets, are not reported for the sake of brevity and are available from the authors upon request.

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

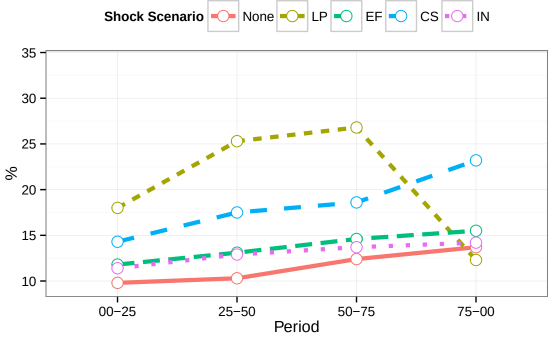
Figure 6: Economic performances under climate shocks by time slices. LP: Labour Productivity shocks ; EN: Energy Efficiency shocks; CS: Capital Stock shocks; IN: Inventories shocks.



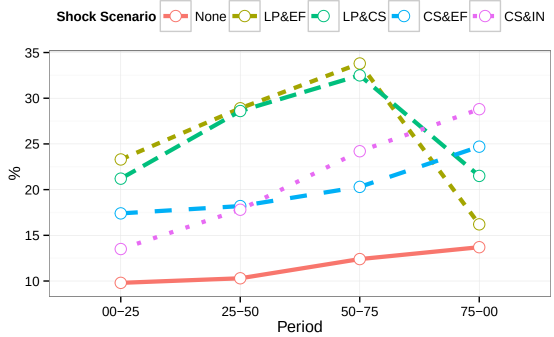
(a) Output growth; shocks un-combined.



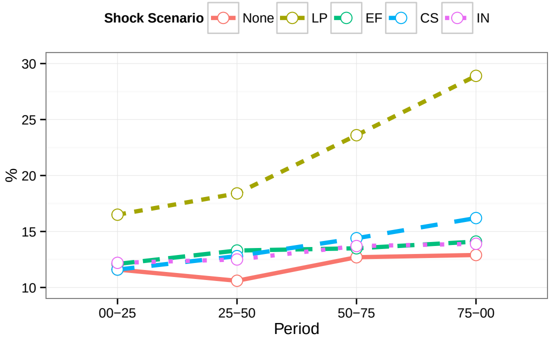
(b) Output growth; shocks combined.



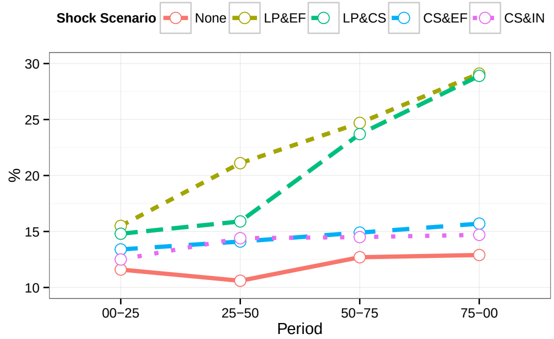
(c) Likelihood of crises; shocks un-combined.



(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.

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-schocks 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 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.

Acknowledgments

FL acknowledges financial support from European Union FP7 grant agreement No. 603416 - Project IMPRESSIONS. GD acknowledges financial support from EU FP7 Project IMPRESSIONS and from European Union's Horizon 2020 grant agreement No. 640772 - Project DOLFINS and No. 649186 - Project ISIGrowth. MN acknowledges financial support from EU H2020 Projects DOLFINS and ISIGrowth. AR acknowledges financial support from EU FP7 Project IMPRESSIONS and EU H2020 Projects DOLFINS and ISIGrowth. AS acknowledges financial support from EU FP7 Project IMPRESSIONS and EU H2020 Project ISIGrowth. The authors are indebted with Valentina Bosetti, Giorgio Fagiolo, Jill J ager, Mattia Guerini, Paula Harrison, Antoine Mandel, Irene Monestarolo and Willi Semmler for valuable comments and discussions that improved the quality of the paper. The authors thank also all the participants to the seminars series at PSE-Université Paris 1 Panthéon-Sorbonne (Paris) and Fondazione Eni Enrico Mattei (FEEM, Milan) and to the following conferences or workshops: WEHIA 2015 (Nice), EMAEE 2015 (Maastricht), WEHIA 2016 (Castellon), CEF 2016 (Bordeaux), Annual Meeting of the International Schumpeter Society 2016 (Montreal), the ISEE Workshop on Agent-based Modelling in Ecological Economics 2016 (Berlin), iEMS 2016 (Toulouse), 50$^{\text{th}}$ SPRU Anniversary Conference, Crisis2016 (Ancona), EAEPE 2016 (Manchester) and the first Hamburg Workshop on Agent-based Modeling of Environmental Challenges and Climate Policy (Hamburg). All the usual disclaimers apply.

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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 $A^k_{i,\tau}$ with $k = \{L, EE, EF\}$, which represent the technical features of the machine produced, and $B^k_{i,\tau}$, which represent the features of the production technique employed by firm i, with τ being the technology vintage. Firms define their price by applying a fixed mark-up ($\mu_1 > 0$) on their unit cost of production defined by the nominal wage, nominal cost of energy, labour productivity, energy efficiency and, eventually, a carbon tax. Capital-good firms can increase both their process and product technology levels via (costly) innovation and imitation. Indeed, R&D expenditures, defined in each period as a fraction of past sales are split between both activities according to the parameter $\xi \in [0, 1]$.

The innovation process has two steps: first a random draw from a Bernoulli distribution with parameter $\vartheta^{in}_i(t) = 1 - \exp^{-\varsigma_1 INNOV_i(t)}$ 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 ($\vartheta^{im}_i(t) = 1 - \exp^{-\varsigma_2 IMIT_i(t)}$) 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^d_j depends upon adaptive expectations $D^e_j = f[D_j(t-1), D_j(t-2), ..., D_j(t-h)]$, desired inventories ($N^d_j$), and the actual stock of inventories (N_j):

$$Q_j(t)^d = D^e_j(t) + N^d_j(t) - N_j(t), \tag{34}$$

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

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

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]

$$EI_j^d(t) = K_j^d(t) - K_j(t). \tag{35}$$

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 $l_j(t)$:

$$E_j(t) = -\omega_1 p_j(t) - \omega_2 I_j(t), \tag{36}$$

where $w_{1,2} \geq 0$.[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 finally linked to their competitiveness through a "quasi" replicator dynamics:

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

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

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

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

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

where $c_j(t)Q_j(t)$ 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 $k > 0$:

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

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:

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

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):

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

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 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).

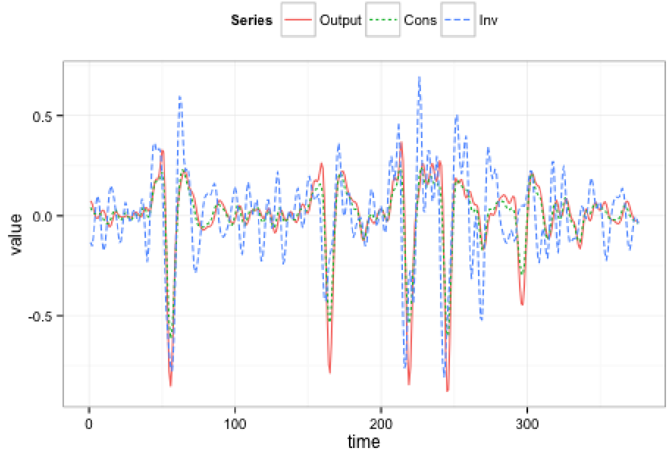
Table 7: Auto-cross correlations between output and main macroeconomic aggregates. Bandpass-filtered (6,32,12) series. Average auto-cross correlations from a Monte Carlo of size 100. Monte Carlo standard deviations are reported below each coefficient.

	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

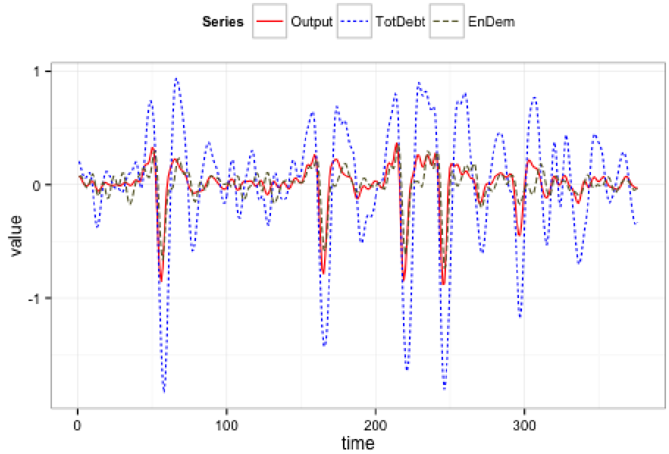
Here we also check whether the emissions pathways generated by the model deliver reasonable results in terms of projected global mean surface temperature. Figure 3 in the main text shows the dynamics of temperature along the whole time span for each of the runs used in a typical Monte Carlo ensemble 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

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

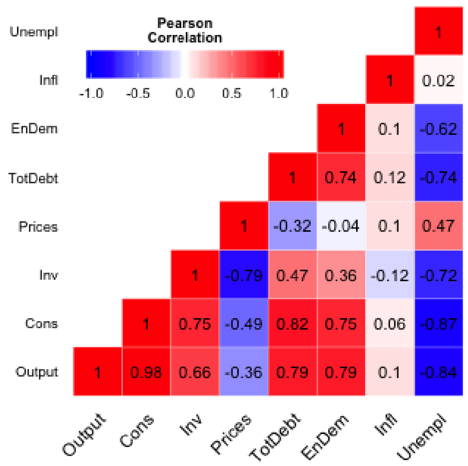
Figure 7: Filtered series and their correlation structure. Panel 7a and Panel 7b presents the behaviour of selected Bandpass-filtered (6,32,12) series for a randomly chosen Monte Carlo run. Panel 7c presents the correlation structure emerging from filtered series and refers to a Monte Carlo of size 100.



(a) Output, Consumption and Investments.



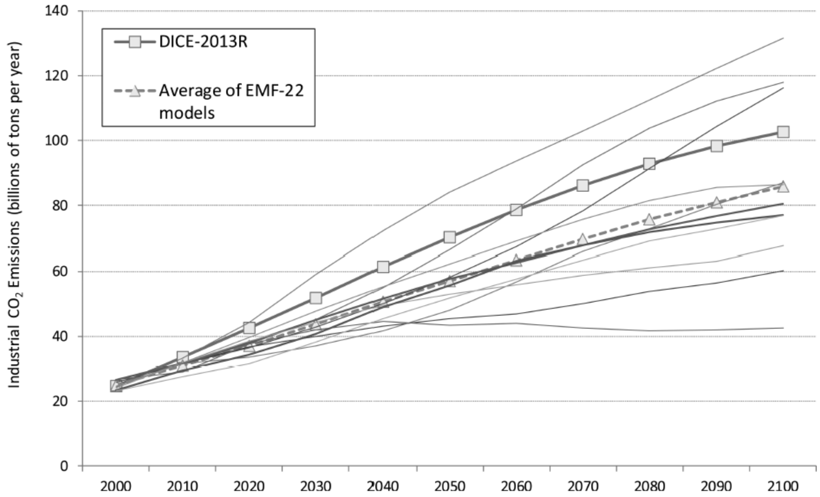
(b) Output, Total private debt, Energy demand.



(c) Correlation structure.

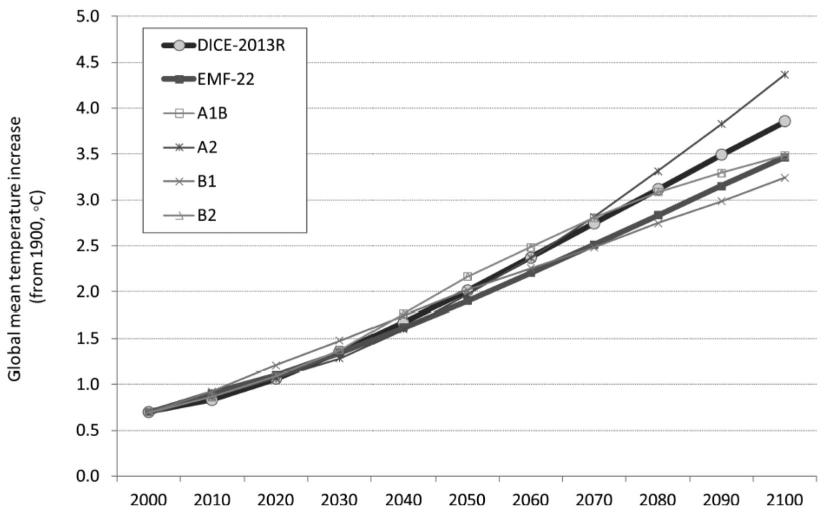
and median values of our projections (reported also in table 1) are slightly higher than counterparts from other models (see also Clarke et al., 2009; Gillingham et al., 2015). A possible reason for this effect is given by the presence, within the carbon cycle (see section 2.3), of different feedbacks loops giving rise to non-linear dynamics.[43]

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



(a) Industrial emissions.

Note: Projected industrial CO_2 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 $GtCO_2$, which can be converted in GtC using the following conversion factor: 1 GtC = 3.67 $GtCO_2$.



(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 CO_2 concentrations from the EMF-22 models. These are then combined with estimates of land-use CO_2 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 ETSAPTIAM, FUND, GTEM, MERGE Optimistic, MERGE Pessimistic, MESSAGE, MiniCAMBASE, POLES, SGM, and WITCH.

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

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 $\Delta \bar{AB}$ weight	ψ_1	1
Wage setting Δcpi weight	ψ_2	0
Wage setting ΔU weight	ψ_3	0
R&D investment propensity (industrial)	ν	0.04
R&D allocation to innovative search	ξ	0.5
Firm search capabilities parameters	$\zeta_{1,2}$	0.3
R&D investment propensity (energy)	ξ_e	0.01
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)	$[\underline{\chi}_1, \bar{\chi}_1]$	$[-0.15, 0.15]$
New customer sample parameter	$\bar{\omega}$	0.5
Desired inventories	l	0.1
Physical scrapping age (industrial)	η	20
Physical scrapping age (energy)	η_e	80
Payback period (industrial)	b	3
Payback period (energy)	b_e	10
Initial (2000) share of green energy		0.1

Table 9: Climate box main parameters and initial conditions.

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

A walk on the wild side: transition to sustainable growth in an agent based integrated-assessment model

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January 20, 2017

Abstract

In this document we briefly describe the application of the DSK model to the analysis of endogenous transitions from a fossil-fuel (dirty) oriented energy production system to a renewable (green) energies one. The model is described in details and a series of exercises under different climate shock scenarios are performed.

The analysis of transitions from fossil-fuel to low-carbon technologies is a fundamental step in the understanding of the triggers, likelihood and impact of moving towards a different production system under different starting scenarios. The DSK model constitutes a viable platform to perform such an analysis. In particular, DSK accounts for endogenous technical change both in the industrial and the energy sectors. In the latter case, decisions on energy production are made on the basis of generation costs. Revenues are then partially reinvested in R&D activities and, specifically, there is a parameter controlling for the share of R&D spending in green and fossil-fuel technologies. By simply linking such parameter to the previous sales of dirty and green energy, it is possible to study the process of diffusion of low-carbon energy-technologies, together with the aggregate impacts of such a phenomenon

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on the economy and the climate. We assume that the share of R&D investment in green (or dirty) technologies is equal to the quota of previous period energy sales from that technology. This reflects the common idea that market size might play some role in shaping the direction of technical change and that investments tend to cumulate on the prevailing areas. In particular, we notice that, under endogenous R&D investment decisions, the model produces a non-ergodic behaviour characterized by two statistical equilibria. In the first case, we find a carbon intensive lock in where the share of energy produced with renewable technologies approaches zero and, after having reached this bound, stays there until the end of the simulation. In the second case, instead, a transition to green energy technologies occurs and the latter happens to persistently dominate the market.

1 The Model

1.1 Model Structure

Our model is composed by a complex economy and a climate box. They evolve simultaneously and the links between the two are modelled non-linearly and stochastically. Figure 1 provides a graphical representation of the DSK model. The economy is build on Dosi et al. (2010, 2013) and is composed by two vertically separated industrial sectors, where firms are fuelled by an energy sector and receive loans from a unique central bank. Firms invest in R&D and innovate to improve the performances of the machines they produce in terms of productivity, energy-efficiency and environmental friendliness. In particular, both the energy and industrial sectors emit CO_2, whose concentrations in the atmosphere affect the evolution of the climate. Specifically, we model a carbon cycle characterized by feedbacks loops in the relationship with the Earth's radiative forcing and the global mean surface temperature. The effects of an increase in Earth's temperature on the economic system is captured by a stochastic disaster generating function. Under a warming climate the probability of large shocks in labour productivity and firms' capital stock 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; rather, it modifies the structure of the stochastic process characterizing economic growth.

1.2 Consumption and capital good sectors

Our economy is mainly composed by a capital-good and a consumption-good sectors, which are vertically related by the exchange of machines. Firms in the capital-good industry produce machine-tools using labour and energy. They innovate and imitate in order to increase both labour productivity and energy efficiency of the machines they sell to the consumption-good firms as well as to reduce their own

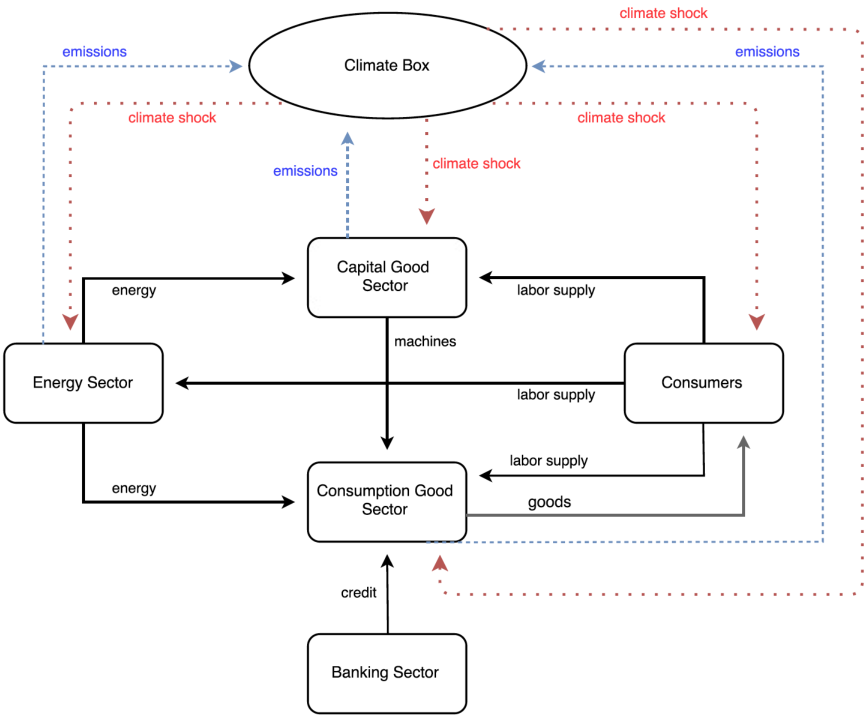


Figure 1: Graphical representation of the DSK model.

production costs. However, innovation and imitation are costly processes and firms need to invest in R&D activities a fraction of their past sales. Technical change influences all the three dimensions that characterize machines in our model, namely, *productivity of labour*, *energy-efficiency* and *environmental-friendliness*. In particular, each production technique and manufactured machine of vintage τ relative to firm i is represented by a set of six coefficients $(A^k_{i,\tau}, B^k_{i,\tau})$ where $k \in \{L, EE, EF\}$. The apex L refers to labour productivity. $A^L_{i,\tau}$ stands for the productivity of the machine-tool manufactured by i for the consumption-good industry, while $B^L_{i,\tau}$ is the productivity of workers employing the production technique used by firm i. The apex EE, instead, refers to energy-efficiency. Therefore, $A^{EE}_{i,\tau}$ represents the output per energy unit obtained by a consumption-good firm using the machine-tool produced by i and $B^{EE}_{i,\tau}$ is the corresponding ratio characterizing i's production technique. Given the monetary wage which is paid to workers at a given instant in time, $w(t)$, and the current cost of energy, $c^{en}(t)$, the unitary cost of production for capital-good firm i is given by

$$c_i^{cap}(t) = \frac{w(t)}{B^L_{i,\tau}} + \frac{c^{en}(t)}{B^{EE}_{i,\tau}}. \tag{1}$$

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

$$c_j^{con}(t) = \frac{w(t)}{A^L_{i,\tau}} + \frac{c^{en}(t)}{A^{EE}_{i,\tau}}. \tag{2}$$

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[1] In what follows we focus on GHGs and CO_2 in particular, as they have been identified, by far, as the major drivers of climate change (IPCC, 2013). Hence, $A^{EF}_{i,\tau}$ refers to the environmental friendliness of the machine-tool produced by firm i, while $A^{EF}_{i,\tau}$ to that of 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 and split the amount invested between search for innovation and attempts to imitate more technologically advanced competitors. As in Dosi et al. (2010), both innovation and imitation are modelled as two step processes. The first one captures the stochastic nature of technical change (add references) and determines the access to the subsequent phase through a draw from a Bernoulli distribution where the amount invested in R&D affects the likelihood of success. The second step determines the size of the technological advance. In the case of imitation, firms accessing the second step are given the opportunity to copy characteristics of production techniques and machines of the closest competitor in the technological space[2] The second step for innovation, instead, entails an additional stochastic component. In particular,

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

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

and

$$A^{EF}_{i,\tau+1} = A^{EF}_{i,\tau}(1-\chi^{EF}_{A,i}) \tag{5}$$

$$B^{EF}_{i,\tau+1} = B^{EF}_{i,\tau}(1-\chi^{EF}_{B,i}), \tag{6}$$

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

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

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

cessful innovation, the new vintage of production techniques and machines will be characterized by a specific novel combination of labour productivity, energy-efficiency and environmental friendliness. Following our characterization of the latter, technological advancements reduce the amount of pollutants per unit of energy used in the production process, as shown by equations (5) and (6).

Consumer good-firms produce a homogeneous good using their stock of machines, energy and labour under constant returns to scale. Then, consumers spend all their available income buying good which is produced. Firms plan their production according to adaptive demand expectations. They decide on their desired production level on the basis of expected demand, desired inventories and their stock of inventories. Whenever the capital stock is not sufficient to produce the desired amount, they invest in order to expand their production capacity, and may thus acquire machines of a more recent vintage than the ones they already have. Machines are supplied by capital-good firms and labour productivities in the consumption-good industry evolve according to the technology embedded in the capital stock of each firm. Consumption-good firms choose their capital-good supplier comparing price, productivity and energy-efficiency of the currently manufactured machine tools they are aware of. The capital-good market is systematically characterized by imperfect information. Machine-tool firms advertise their machines' price and productivity levels by sending *brochures* to a subset of consumption-good firms, which in turn choose the machines with the lowest price and unit cost of production. In particular, let $\Xi_i(t)$ the set of all machines' vintages firm j have at time t. Then a machine of vintage τ is replaced with a new one if

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

where p^{new} and c^{new} are the price and unitary cost of production associated to the new vintage of machines and b is a parameter determining firms' reluctance to invest. Machine production is a time-consuming process: consumption-good firms receive the ordered machines at the end of the period. Gross investment of each firm is the sum of expansion and replacement investments. Aggregate investment is just the sum of the investments of all consumption good firms. Pricing follows a variable mark up rule. Firms sets the price of the final good they produce according to

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

where

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

with $0 \leq \upsilon \leq 1$. In equation (9), $f_j(t)$ indicates the market share of firm j at time t. Consumption-good firms have to finance their investments as well as their production. In line with a large body of literature (Stiglitz and Weiss, 1981; Greenwald and Stiglitz, 1993) we assume imperfect capital markets. Firms access firstly their net worth and if the latter does not fully cover total production and investment costs, they borrow external funds from the bank. However, firms have limited borrowing capacity: the ratio between debt and sales cannot exceed a maximum threshold depending on the firms' past sales. Moreover, credit rationing might occur. The bank allocates total credit to each firm in the consumption-good sector on a pecking order basis, according to the ratio between net worth and sales. In particular, it first ranks firms on the basis on their net worth-to-sales ratio, and starts to satisfy their demand. If the total credit available is insufficient to fulfill the demand of all the firms in the pecking order list, some firms that are lower in the raking are credit rationed. Note that only firms that are not credit-rationed can fully satisfy their investment plans employing their stock of liquid assets first and then their borrowing capacity. The maximum amount of credit available in the economy is set above the sum of firms' deposits by a multiplicative rule (Dosi et al. (2013)). Implicitly, we assume there is a Central Bank allowing the bank to lend money up to a threshold that is a multiple of the firms' deposits.

1.3 The energy module

Energy production is performed by a profit-seeking, vertically-integrated monopolist through power plants using green and dirty technologies. The 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).

The energy monopolist produces and sells electricity to firms in the capital-good and consumption-good industries, on demand. Hence, at the beginning of period t, electricity consuming firms send orders that in aggregate amount to $D_e(t)$. The non-storable nature of electricity implies that the demand-supply balance must be continuously guaranteed, i.e. it must always be $Q_e(t) = D_e(t)$. Profits of the energy monopolist at the end of period t are equal to

$$\Pi_e(t) = S_e(t) - PC_e(t) - IC_e(t) - RD_e(t) \tag{10}$$

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

1.3.1 Electricity producing technologies and costs

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

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

where $p_f(t)$ is the price of fossil fuels, exogenously determined on a international market.[3] Notice that electricity production is a highly capital-intensive process, which mainly requires power generation assets and resources (be them fossil fuels or renewable sources), while the labour input is minimal. We can thus assume away labour from electricity production.

The total production costs depends on which plants are used. If the monopolist wishes to economize on costs, it will be better off running all of its green plants and switching on the dirty plants only if the green capacity is insufficient to satisfy demand. Even then, the cheapest dirty plants will be used first.[4]

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

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

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

total production cost is

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

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

1.3.2 Revenues

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

$$p_e(t) = \mu_e \tag{13}$$

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

$$p_e(t) = \overline{c}_{de}(\tau, t) + \mu_e \tag{14}$$

if $D_e(t) > K_{ge}(t)$, where $\overline{c}_{de}(\tau, t) = \max_{\tau \in IM} c_{de}(\tau, t)$. By setting a markup on this unit cost level, the energy producer gains a positive net revenue on all infra-marginal plants.[5]

A monopolistic producer may be tempted to arbitrarily increase the selling price beyond any limit, but this usually does not occur - except for some very short-lived spikes - because producers fear regulatory intervention, wish to discourage entry, or there is a price cap set by the regulatory agency to formally constrain the exploitation of market power opportunities. In some countries, in fact, energy production is entrusted to a regulated monopolist, who would have face the obligation to set $\mu_e = 0$, i.e. to sell at a cost-reflective price.

1.3.3 Expansion and replacement investments

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

The capacity stock $K_e(t)$ is defined as the sum of the capacities of all power plants across technologies (green, dirty) and vintages. The capacities of individual plants are normalized to one; $g_{de}(\tau, t)$ denotes

[5] Other empirically observed ways of exploiting market power include withholding relatively cheap plants and causing network congestion, but we believe that modeling market power through markups is a simple and workable way of encompassing all these practices.

the absolute frequency of vintage-τ dirty plants (already defined above), and $g_{ge}(\tau, t)$ is the same for green plants. Then the capacity stock is equal to

$$K_e(t) = \sum_\tau g_{de}(\tau, t) + \sum_\tau g_{ge}(\tau, t) \tag{15}$$

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

$$\overline{Q}_e(t) = \sum_\tau g_{de}(\tau, t) A^\tau_{de} + \sum_\tau g_{ge}(\tau, t) \tag{16}$$

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

$$EI_e(t) = K^d_e(t) - K_e(t) \tag{17}$$

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

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

$$\underline{IC}_{ge} \leq b\underline{c}_{de} \tag{18}$$

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

$$EC_e(t) = \underline{IC}_{ge} EI_e(t) \tag{19}$$

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

1.3.4 R&D expenditures and outcomes

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

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

$$RD_{ge}(t) = \xi S_{ge}(t-1) \tag{20}$$

and

$$RD_{de}(t) = \xi S_{de}(t-1). \tag{21}$$

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

The innovative search in the two paths is successful with probabilities $\theta_{ge}(t)$ and $\theta_{de}(t)$, conditioned on the R&D investment:

$$\theta_{ge}(t) = 1 - e^{-\eta_{ge} IN_{ge}(t)} \tag{22}$$

and

$$\theta_{de}(t) = 1 - e^{-\eta_{de} IN_{de}(t)} \tag{23}$$

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

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

$$IC^{\tau}_{ge} = IC^{\tau-1}_{ge} x_{ge} \tag{24}$$

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

$$A^{\tau}_{de} = A^{\tau-1}_{de}(1 + x^{A}_{de}) \qquad em^{\tau}_{de} = em^{\tau-1}_{de}(1 - x^{em}_{de}) \tag{25}$$

where x^A_{de} and x^{em}_{de} are independent random draws from a Beta distribution.[6]

1.3.5 Liquid assets

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

$$NW_e(t) = NW_e(t-1) + \Pi_e(t) - cI_e(t) \tag{26}$$

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

1.4 The climate box

Our climate box links CO_2 emissions with atmospheric concentrations of carbon and the dynamics of Earth's mean surface temperature. These relationships are modelled non-linearly through a core carbon cycle characterized by feedbacks and based on Sterman et al. (2012, 2013). The underlying purpose of this part of the model is to avoid a complex and detailed description of the physical and chemical relations governing climate's evolution but, at the same time, to capture its major features paying particular attention to the inclusion of feedbacks that might give rise to non-linear dynamics.[7]

1.4.1 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). Atmospheric CO_2 is determined in each period by the interplay of different factors. It is increased by anthropogenic emissions, exchanges with the oceans and natural emissions from the biosphere. On the other side, CO_2 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), which is modelled here as the flux of carbon from the atmosphere to biomass, grows logarithmically with stocks of CO_2 (Wullschleger et al., 1995) and is negatively affected by temperature's increase.

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

[7] These feedbacks are generally overlooked by standard climate-economy models even though there is ample evidence of their importance in accelerating global warming (see discussions in next paragraphs). Our 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).

In particular,

$$NPP(t) = NPP(0) \left(1 + \beta_C \log \frac{C_a(t)}{C_a(0)}\right) (1 - \beta_{T_1} T_m(t-1)) \tag{27}$$

where $C_a(t)$ represent 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 CO_2 fertilization feedback,[8] 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 an important climate-carbon feedback. The role of warming on biosphere' uptake of carbon is still object of debate and strongly depends on local elements (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. Along this line and in accordance with recent findings (Zhao and Running, 2010), we model a negative effect of warming on NPP. As in Sterman et al. (2012) we employ a simple linear formulation of the temperature feedback. The linear effect can be thought of as the first term in a Taylor series approximation for the full non-linear impact of warming.

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).[9] 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:

$$C_m(t) = C_m^*(t) \left[\frac{C_a(t)}{C_a(0)}\right]^{\frac{1}{\xi}} \tag{28}$$

where C_m^* is the reference carbon concentration in the mixed layer, $C_a(t)$ and $C_a(0)$ are the concentrations of atmospheric carbon at time t and at the initial point of the simulation, and ξ is the buffer (or Revelle) factor.[10] 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

[8] Loosely speaking, the fertilization feedback refers to the phenomenon of increasing biosphere's carbon uptake due to the stimulus that CO_2 concentrations in the atmosphere exerts on vegetation productivity (Allen, 1990; Allen and Amthor, 1995; Matthews, 2007).

[9] Our representation of the oceans resembles that in Nordhaus (1992).

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

as its concentration in the atmosphere increases:

$$\xi(t) = \xi_0 + \delta \log \left[\frac{C_a(t-1)}{C_a(0)} \right] \tag{29}$$

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

Another relevant climate-carbon cycle feedback concerns the negative effect of warming on the seawater solubility of CO_2 (Fung, 1993; Sarmiento et al., 1998), an effect which has been shown to accelerate climate change (Cox et al., 2000). As in the previous case we approximate this feedback to a first order term:

$$C_m^*(t) = C_m(0)[1 - \beta_{T_2} T_m(t-1)] \tag{30}$$

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

Net flux of carbon through the oceans is determined by the relative concentrations of carbon in the mixed and deep layers and a diffusion parameter according to

$$\Delta C_{ij}(t) = k_{eddy} \frac{\left[\frac{C_i(t-1)}{d_i} - \frac{C_j(t-1)}{d_j} \right]}{\langle d_{ij} \rangle} \tag{31}$$

where d_i is the thickness of layer i, $\langle d_{ij} \rangle$ is the mean thickness of layers i and j, and k_{eddy} is the eddy diffusion parameter.[11] The flux of carbon though atmosphere, biosphere and oceans affects the heat transfer across the system and, hence, the dynamics of Earth surface mean temperature.

1.4.2 Global Warming

Global mean surface temperature is determined by the heat content of the surface and mixed layer of the oceans, which are aggregated into a single compartment. To model the behaviour of temperatures in the different layers we build on Schneider and Thompson (1981) and Nordhaus (1992). The heat content of the different layers is modulated by their reciprocal exchanges and, with respect to the upper compartment (atmosphere and surface oceans), by the CO_2 radiative forcing.[12] In particular,

[11] 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 spun's movements.

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

$$T_m(t) = T_m(t-1) + c_1 \{F_{CO_2}(t) - \lambda T_m(t-1) - c_3[T_m(t-1) - T_d(t-1)]\} \tag{32}$$

$$T_d(t) = T_d(t-1) + c_4 \{\sigma_{md}[T_m(t-1) - T_d(t-1)]\} \tag{33}$$

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

$$F_{CO_2}(t) = \gamma \log \left(\frac{C_a(t)}{C_a(0)} \right). \tag{34}$$

Equation (34) represents the main link between anthropomorphic emissions, which contribute to increase the concentration of carbon in the atmosphere at any period, and climate change, which is induced by the radiative forcing of atmospheric GHGs. On the other side, global warming exerts two important feedbacks on the dynamics of carbon, affecting its exchanges with the biosphere, equation (27), and the oceans, equation (30).

1.4.3 The timeline of events in the climate box

Events within the climate box follow a precise order in each period. Suppose that time $t-1$ is characterised by certain values for each of the climate variables previously described. Therefore, at the beginning of the new period, t, these values are inherited from the past. Moreover, we assume that events in the economy and the climate box happen sequentially with the surface temperature as the last variable to be determined, therefore

1. total emissions produced in period t add to the current stock of atmospheric CO_2 concentrations, thereby modifying the biophysical equilibrium;

2. the increased stock of carbon concentrations affects the oceans marginal capacity to uptake CO_2;

3. carbon exchanges between the atmosphere and both biosphere and oceans take place, with the feedback effects of warming affecting them;

4. the new equilibrium concentration of carbon in the atmosphere, $C_a(t)$, is found;

5. $C_a(t)$ affects the new radiative forcing of GHG;

6. which in turns determines the entity of climate change, that is, the increase in mean surface and upper oceans' temperature;

7. then, 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 introduces the closing block of our model, that is, the presence of feedback between temperature evolution and the economy described so far.

1.5 The structure of climate-economy feedbacks

The climate and the economy are linked through a double relationship. On one hand, a warming climate affects the functioning of the economy along three main channels: the productivity of labour in the consumption and capital good industries, firms' stock of capital and workers health. On the other, production activities of firms and the energy monopolist emit CO_2 in the atmosphere at each time step, thereby increasing its concentration. Total emissions are simply obtained as the sum of emissions in the industrial and energy sides of the economy:

$$Em(t) = \sum_{\tau} \left(\sum_{i} Em^{cap}_{i,\tau}(t) + \sum_{j} Em^{con}_{i,\tau}(t) + Em^{en}_{\tau}(t) \right) \tag{35}$$

where $Em^{k}_{i,\tau}$ is just the emission of CO_2 generated by machine (or plant, in the case of the energy sector) of vintage τ of firm i in sector k. This quantity is 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. Additional CO_2 in the atmosphere increase the radiative forcing and contributes to climate change. Most IAM model the impact of those changes on the economy as aggregated fractional losses of GDP. As well outlined in Pindyck (2013) the choice of how to represent warming-induced damages is the most speculative element of the analysis, both because of lack of robust empirical evidences and usual the neglect of societies' possible adaptation. The usual practice consists in specifying an ad-hoc functional form for the so-called *damage function* with equally ad-hoc parameters.[13] Apart from this arbitrarily, the use of such damage functions brings three additional problematic issues. Firstly, aggregating everything in a loss of final output, models employing them do not distinguish between different types of possible damages; secondly, being in general continuous and smooth in their domain they rule out the treatment of catastrophes, conceived

[13]For 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 function. All these modeling attempts are neither explained, justified or tested.

as extreme and rare damages. Finally, they assume an absolute degree of certainty in the occurrence of the damage; whenever it does materialize an increase in average surface temperature, some output must be destroyed somewhere.

Trying to overcome some of these problems we model the link between climate and the economy differently. In particular, we introduce a stochastic *damage generating function*, which is nothing more than a parametric probability density function for dis-aggregated shocks that endogenously evolve according to the dynamics of the climate. At the end of each period, a draw from this distribution establishes the size of the shock affecting firms and workers. Notably, shocks are heterogeneous across agents, meaning that some firm might be hit by a climate disaster while some other might not.

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

$$f(s; a, b) = \frac{1}{B(a, b)} s^{a-1}(1-s)^{b-1} \tag{36}$$

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

$$a(t) = a_0[1 + \log T_m(t)] \tag{37}$$

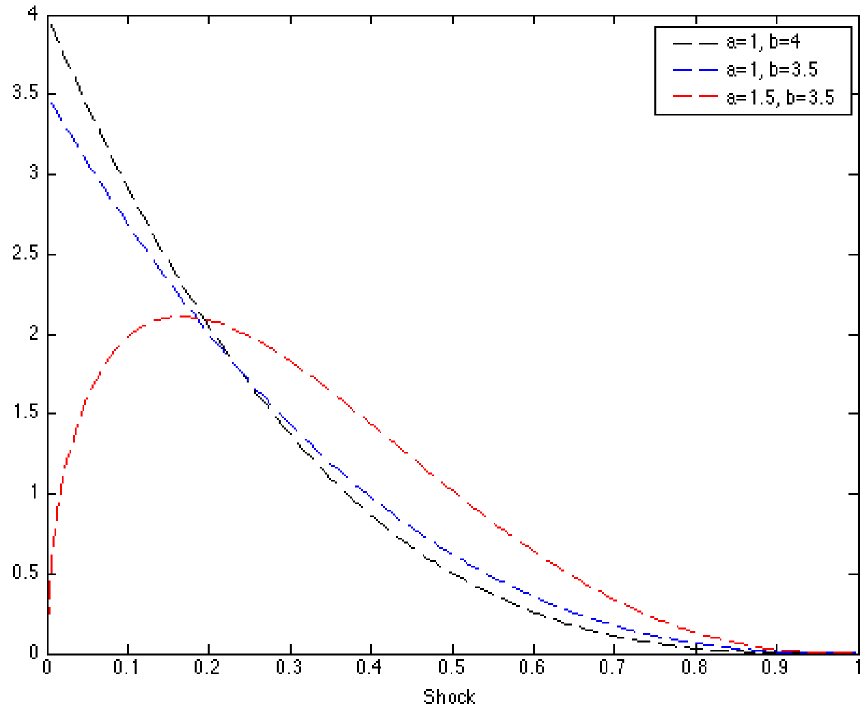
$$b(t) = b_0 \frac{\sigma_{10y}(0)}{\sigma_{10y}(t)} \tag{38}$$

where $\sigma_{10y}(t)$ is a measure of the variability of surface temperatures across the previous decade and a_0, b_0 are positive integers.[14] Equations (37) and (38) shape the disaster generating function as a right-skewed, unimodal distribution such that the mass moves along the positive axis as temperature increases, thereby raising the likelihood of larger shocks. Equation (38) determines the size of the right tail of the distribution and allows to account for the importance of climate variability on natural disasters (Katz and Brown, 1992; Renton et al., 2014). Despite variability has been increasingly recognized as a major driver of climate disasters (Thomalla et al., 2006; IPCC, 2012; Revesz et al., 2014), the majority of models do not even mention it. Figure 2 shows the shape of the density of a Beta for different values of the location (a) and scale (b) parameters.

We account for three possible shocks induced by climate change on the economy. First, a shock

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

Figure 2: Beta density function for different values of a and b.



to labour productivity of machines, plants and production techniques. Although there is a generalized lack of empirical evidences about how climate change directly affects economies' fundamentals (going beyond a well documented negative correlation between temperature and GDP growth), global warming has been shown to consistently impact workers' productivity (Grether, 1973; Pilcher et al., 2002; Niemelä et al., 2002).[15] Second, we consider shocks to firms' stock of capital reflecting the natural idea that extreme climate and weather events, which are typically favoured by warming (Christensen and Christensen, 2003; Diffenbaugh et al., 2005), might destroy physical capital or impede machines to function. Finally, we include climate change-induced shocks to people's health (Basu and Samet, 2002, for a review) and we assume that a fraction of workers becomes unable to work for periods successive to the shock.[16]

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

$$X_{i,\tau}(t) = X'_i(t)[1 - \hat{s}^x_i(t)] \tag{39}$$

where i indexes firms in the economy, $X(t)$ might represent the labour productivity characterizing machines, plants and production techniques, the capital stock or the number of workers in firm i, $\hat{s}^x(t)$ is the time t draw from the disaster generating function relative to X, and X' is the value of X the

[15]The idea that warming reduces the productivity of labour dates back to the ancient Greeks and has been discussed also in Montesquieu (1748)'s *The Spirit of Laws* and Huntington (1915)'s *Civilization and Climate*.

[16]For a nice review of climate and weather impacts on the economy see Dell et al. (2012, section 3).

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	0.031	0.005	Share of emissions from energy sector	0.642	0.361
Likelihood of crises	0.10	0.076	Share of green energy	0.352	0.471
Unemployment	0.09	0.022	Periods green energy above 20%	0.370	0.256
Energy demand growth	0.028	0.002	Emissions growth	0.011	0.001
GDP volatility	0.261	0.011	Consumption volatility	0.168	0.019
Investment volatility	0.301	0.027	Volatility of firm total debt	0.561	0.042
Volatility of energy demand	0.226	0.043	Emissions volatility	0.297	0.033
Emissions at 2100	26.17	9.810	Temperature at 2100	4.38	0.587

Note: All values refer to a Monte Carlo of size 100. Emissions are expressed in GtC, which can be converted in $GtCO_2$ using the following conversion factor: 1 GtC = 3.67 $GtCO_2$. Temperature is expressed in Celsius degrees above the preindustrial level, which is assumed to be 14 Celsius degrees.

shock would have not occurred.

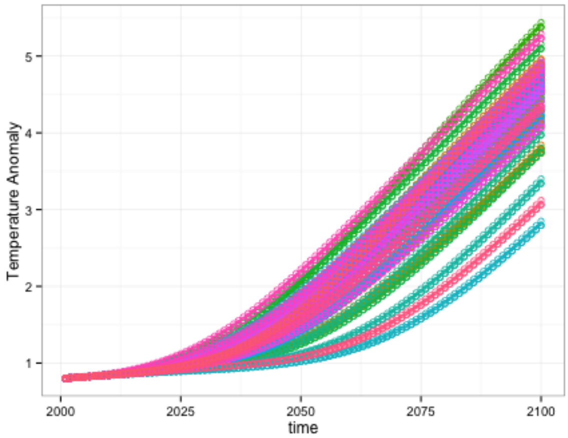
1.6 Model Behaviour and Baseline Configuration

In its baseline (benchmark) configuration the model is run in absence of climate damages and under the parametrization discussed in Lamperti et al. (2017). After having discussed the main properties of the dynamics generated by such a configuration, we introduce three climate shocks scenarios and let the model run on them.

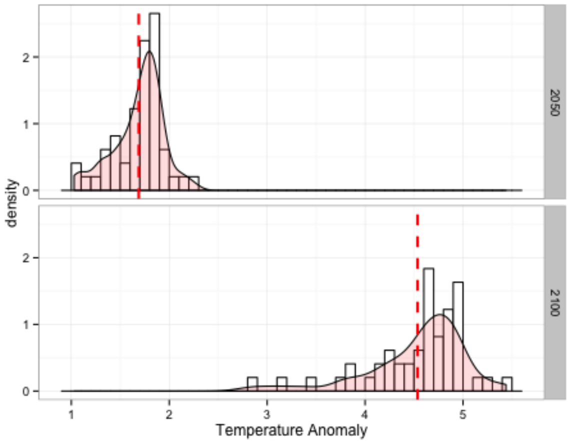
In its benchmark version the model robustly generates endogenous self-sustained growth patterns (see the behaviour of average productivity in figure 3) characterized by the presence of persistent fluctuations and, remarkably, endogenous crises. Furthermore, we see that energy demand and output grow together with emissions, even though the latter exhibit a lower pace (see table 1). This result is quite in line with recent evidence collected in Olivier et al. (2015), where it is showed that emissions at global level grew of about 1% per year in the last decade, in contrast with a much higher pace registered in previous times and notwithstanding a relatively high growth of world output (e.g. 3% in 2014). In addition, final projections of aggregate industrial emissions (average of 26.9 GtC at 2100) are in line with those produced by many other models used by the IPCC Clarke et al. (2009).

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. For a more detailed analysis of the empirical regularities that the model reproduces we refer to Lamperti et al. (2017).

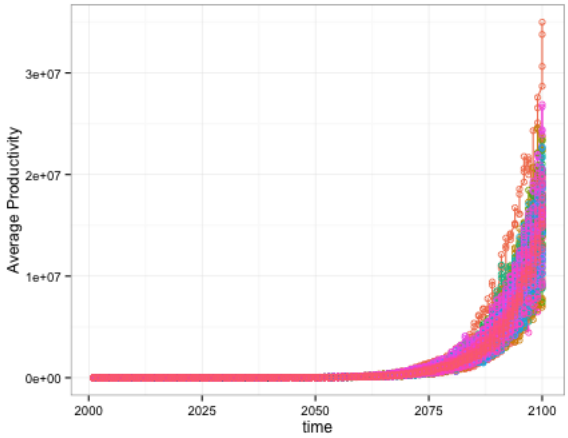
Figure 3: Temperature projections and their density estimates.



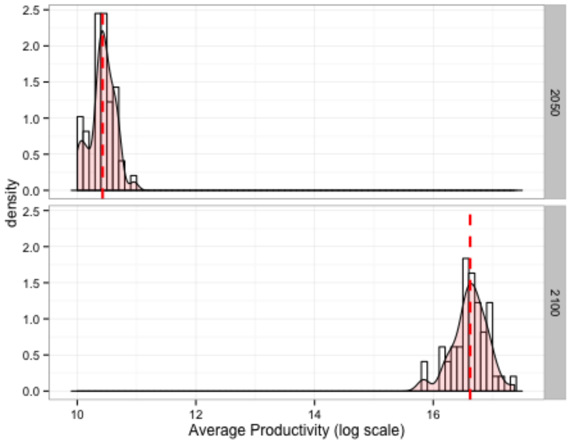
(a) Temperature projections.



(b) Distribution of temperature.



(c) Average firm productivity projections.



(d) Distribution of average firm productivity.

Note: Both graphs refers to a Monte Carlo of size 50. Red dashed lines in panel 3b indicate mean values. In panel 3d the x-axis is in logarithmic scale.

2 Transition towards Green Energy Technologies

The model produces a non-ergodic behaviour characterized by two statistical equilibria (figure 4 for a graphical representation).[17] In the first case we find a *carbon intensive lock in* where the share of energy produced with renewable technologies approaches zero and, after having reached this bound, keeps there until the end of the simulation. In the second case, instead, a *transition to green* energy technologies occurs and they happen to persistently dominate the market.[18] The characterizing features of the two endogenous scenarios are examined by means of Monte Carlo simulations. In particular, we

[17]Tests on the presence of statistical equilibrium on a set of model variables including emissions and output are available from the authors.

[18]More precisely, we say that *carbon intensive lock in* takes place in a given run if the share of green energy never touches the 50% and, from some point on, keeps below 20% reaching the zero lower bound before the end of the simulation; conversely, we define a *transition to green* as a run where the share of green energy reaches the 80%, and never fall below 50% afterwards.

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	Burns and Mitchell (1946); Kuznets and Murphy (1966)
with persistent fluctuations	Zarnowitz (1985); Stock and Watson (1999)
SF2 Fat-tailed GDP growth-rate distribution	Fagiolo et al. (2008); Castaldi and Dosi (2009)
	Lamperti and Mattei (2016)
SF3 Recession duration exponentially distributed	Ausloos et al. (2004); Wright (2005)
SF4 Relative volatility of GDP, consumption, investments and debt	Stock and Watson (1999); Napoletano et al. (2006)
SF5 Cross-correlations of macro variables	Stock and Watson (1999); Napoletano et al. (2006)
SF6 Pro-cyclical aggregate R&D investment	Wälde and Woitek (2004)
SF7 Cross-correlations of credit-related variables	Lown and Morgan (2006); Leary (2009)
SF8 Cross-correlation between firm debt and loan losses	Foos et al. (2010); Mendoza and Terrones (2012)
SF9 Pro-cyclical energy demand	Moosa (2000)
SF10 Syncronization of emissions dynamics and business cycles	Peters et al. (2012); Doda (2014)
SF11 Co-integration of output, energy demand and emissions	Triacca (2001); Ozturk (2010); Attanasio et al. (2012)
Microeconomic stylized facts	
SF12 Firm (log) size distribution is right-skewed	Dosi (2007)
SF13 Fat-tailed firm growth-rate distribution	Bottazzi and Secchi (2003, 2006)
SF14 Productivity heterogeneity across firms	Bartelsman and Doms (2000); Dosi (2007)
SF15 Persistent productivity differential across firms	Bartelsman and Doms (2000); Dosi (2007)
SF16 Lumpy investment rates at firm-level	Doms and Dunne (1998)
SF17 Persistent energy and carbon efficiency heterogeneity across firms	DeCanio and Watkins (1998); Petrick et al. (2013)

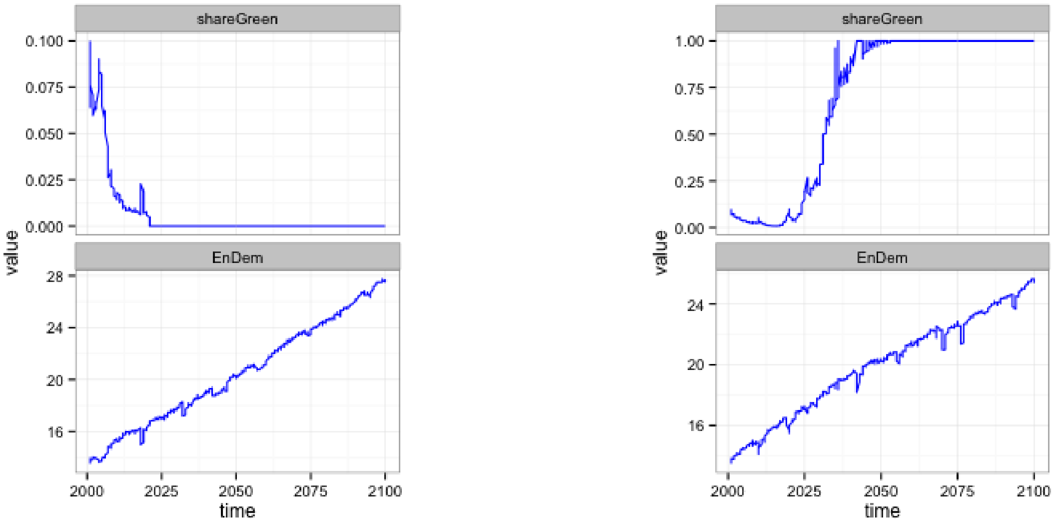
first construct a sub-sample of runs for each of the two equilibria and, secondly, we study the differences between the two with respect to different variables of interest. Our results are collected in 3.

First, we notice that without policy intervention carbon intensive lock in is much more likely than a transition towards green technologies. Interestingly, we distinguish between lock in scenarios occurring before and after the year 2025 (that corresponds to first quarter of the whole simulation time) and we find that the vast majority (90%) of them take place early and rapidly. A similar feature characterizes the transition scenario; when green technologies start to diffuse and reach some critical mass their relative share with respect to dirty ones suddenly increases and they manage to saturate the market, showing a typical S-shaped curve. According to our results, it is only when the transition is sufficiently early that temperature projections do not exceed the +2 degree threshold. From a macroeconomic perspective we also notice that transitions are associated with higher growth of the economy and lower levels of unemployment. The reason behind such results lies in the fact that renewable energy power plants construction requires larger investments than fossil fuel oriented ones, in line with empirical evidence (EIA, 2013).

2.1 Experiments

In order to investigate the behaviour of the model under the two statistical equilibria and to better disentangle the issues related to the likelihood of transition, we perform a series of computational exercises.

Figure 4: Share of renewable (green) energy and energy demand under lock in and transition scenarios.



(a) Carbon intensive energy technology lock in.

(b) Transition to renewable energy technology.

Note: Behaviour of selected variables from a randomly chosen Monte Carlo run within the same scenario. Energy demand in logs.

Table 3: Likelihood of transition in the baseline configuration and main features of the different endogenous scenarios. All values refer to the average computed on the sub-sample of runs from a Monte Carlo of size 100 that are classified in each scenario. Standard deviations in different sub-samples are reported below each coefficient.

	Carbon intensive lock in		Transition to green	
Likelihoods	82%		18%	
	before 2025 90%	after 2025 10%	before 2075 91%	after 2075 9%
Output growth	3.16%	3.14%	3.27%	3.18%
	0.001	0.002	0.001	0.008
Unemployment	11.4%	12.1%	9.12%	10.0%
	0.016	0.020	0.019	0.012
Emission growth	1.22%	1.25%	0.77%	0.96%
	0.001	0.002	0.001	0.002
Emissions at 2100	28.64	30.12	18.22	23.13
	1.761	2.237	1.52	2.172
Temperature at 2100	4.59	4.91	1.75	2.68
	0.103	0.178	0.123	0.153

First, we consider 3 climate shock scenarios:

- Aggregate shocks on GDP as in Nordhaus and Sztorc (2013); Nordhaus (2014)
- *Individual labour productivity (LP) shocks.* Labor productivity ($A^L_{i,\tau}$ and $B^L_{i,\tau}$) falls by a factor that varies across firms, as climate change negatively impacts on workers' operative and cognitive

tasks (Seppanen et al., 2003, 2006).

- *Individual energy efficiency (EF) shocks.* Firm-level energy efficiency ($A^{EE}_{i,\tau}$ and $B^{EE}_{i,\tau}$) 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).

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Then, in each of these scenarios, we let price of fossil fuel (p_f) vary in a way that the initial relative cost advantage of dirty to clean energy technology ranges between 1% and 40%. In particular, we test 9 cases where the per-period unitary energy generation cost in year 2000 of clean technology is larger than the corresponding costs with dirty technology by 1%, 5%, 10%, 15%, 20%, 25%, 30%, 35% and 40%. In the baseline configuration the relative cost advantage is equal to 20%. These exercises are equivalent to the introduction of a tax or subsidies on fossil fuel use increasing or reducing their unitary price. Results of our experiments are reported in table 4 and in a series of figures (**??**, **??**, **??**) and can be summarized as follows

- Under business-as-usual, the likelihood of transition is remarkably low. We find that endogenous transitions towards the good equilibrium where green energy technology dominates the market are possible but, in absence of policy intervention, the likelihood of such an event does not exceed 18

- The presence of climate damages might either increase or reduce the likelihood of transitions. We consider climate damages in two different ways. On one side we take the standard aggregate perspective embraced by the majority of IAMs. On the other, heterogeneous climate damages that target labour productivity or energy efficiency are considered. In the first case, the likelihood of transition is exactly the same as the case of no damages, since they only affect aggregate potential output. In the second case, we find that labour productivity shocks might increase the likelihood of transitions (with respect to the case of aggregate damages), while the opposite happens for energy-efficiency shocks. The main channel of these effects is represented by the size of the final demand for energy (details in Annex I).

- The price of fossil fuels non-linearly influences the likelihood of transition. We find that an increase in the initial price of fossil fuels might increase the likelihood of a transition. However, such an effect is largely non-linear. Given the initial backwardness of clean technologies productivity and the cumulative nature of the technical change process, small variations of the fossil fuel price have a remarkable low impact on inducing the transition, while for moderate/high increases the likelihood improves substantially. This result supports the idea that policy intervention, in this case aimed at increasing the cost of fossil fuels, needs to be substantial in order to significantly affect the environmental sustainability of the production system.

- Climate change can be kept under the + 2 degree target only if the transition occurs before 2025. We find that the timing of the transition is crucial in determining the level of temperature anomaly at the end of the century. Our results point to a transition that should take place within 2025-2030 in order to meet the + 2 degrees target. We also find that the temperature will rise above the + 3 degree with reasonable likelihood in case the transition materializes after 2075.

Table 4: Likelihood of transition, economic performances and emissions under the different climate shock scenarios. Aggregate shocks use the damage function in Nordhaus and Sztorc (2013) and target aggregate output. Labour productivity and energy efficiency shocks target individual firms.

Shock scenario:	Transition likelihood	GDP growth	Energy growth	Emissions at 2100
Aggregate output	18%	3.18%	3.09%	28.33
	(of which 83% before 2025)	(0.001)	(0.003)	(6.431)
Labour productivity	20%	1.30%	1.16%	25.70
	(of which 69% before 2025)	(0.002)	(0.003)	(4.921)
Energy efficiency	7%	3.12%	3.37%	40.64
	(of which 43% before 2025)	(0.001)	(0.003)	(3.872)

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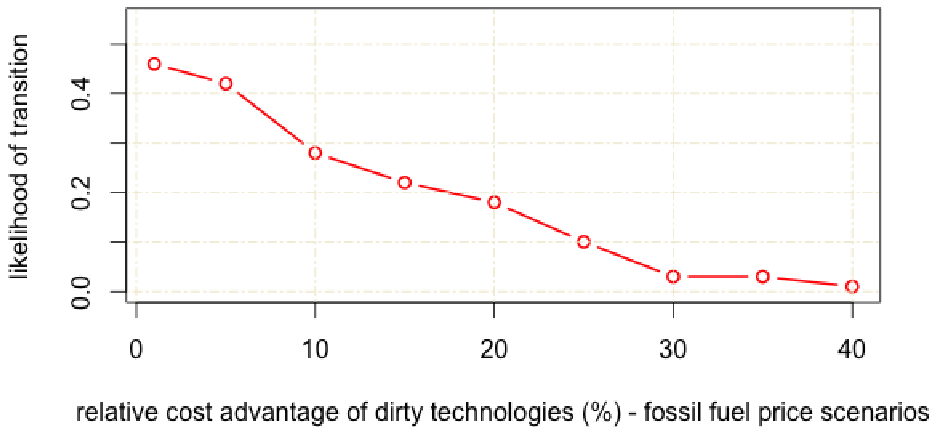
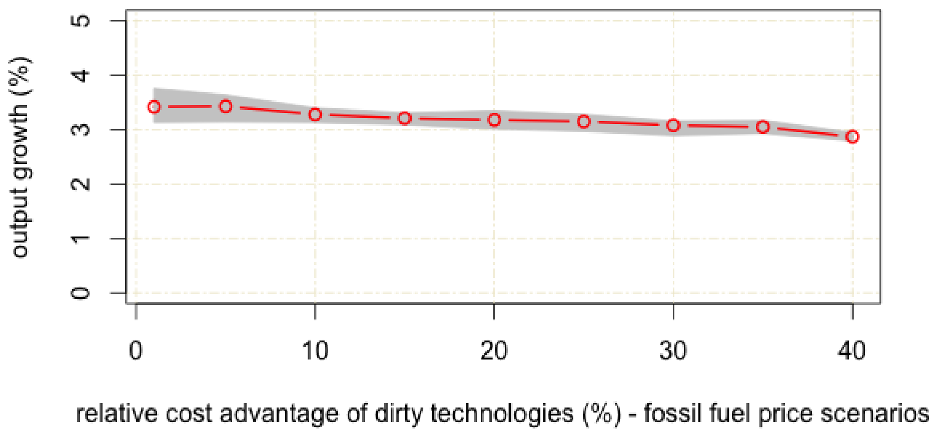
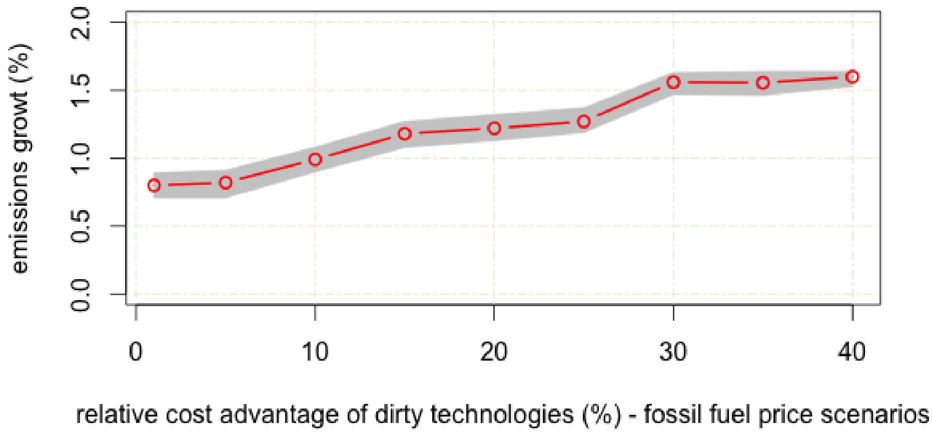
Figure 5: Likelihood of transition, output growth and emissions growth under aggregate climate damages as in (Nordhaus and Sztorc, 2013). MC of size 200, shaded area represents 95% confidence interval.



(a) Likelihood of transition.

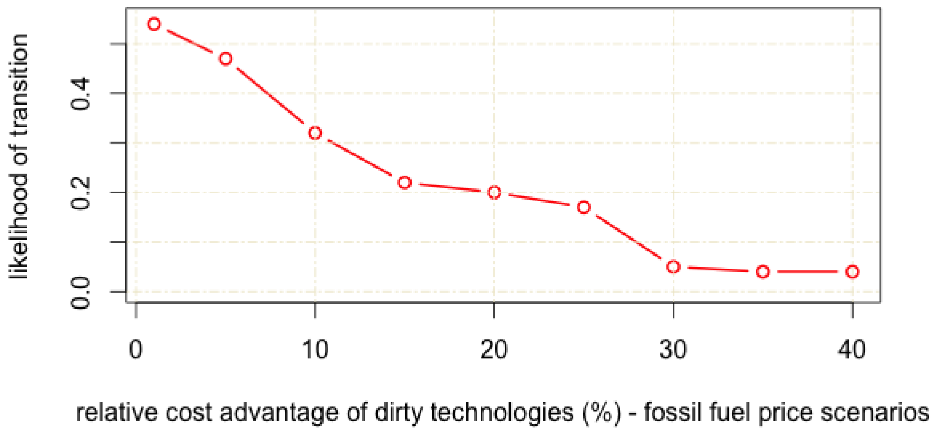


(b) GDP growth.

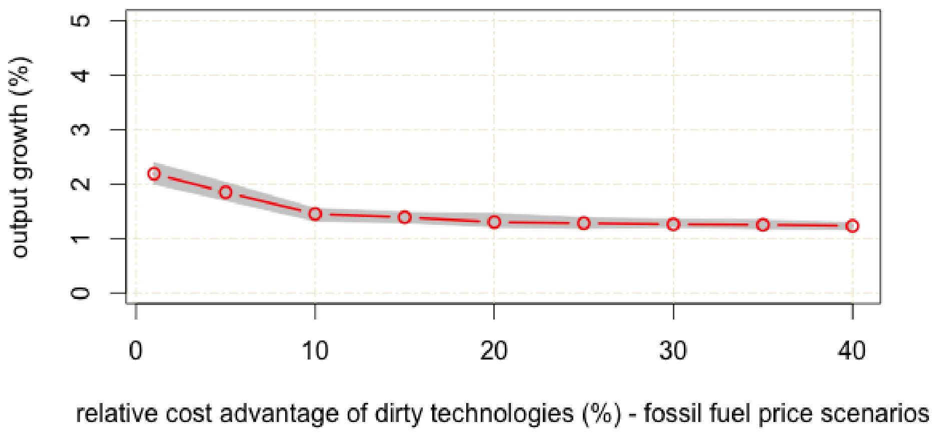


(c) Emissions growth.

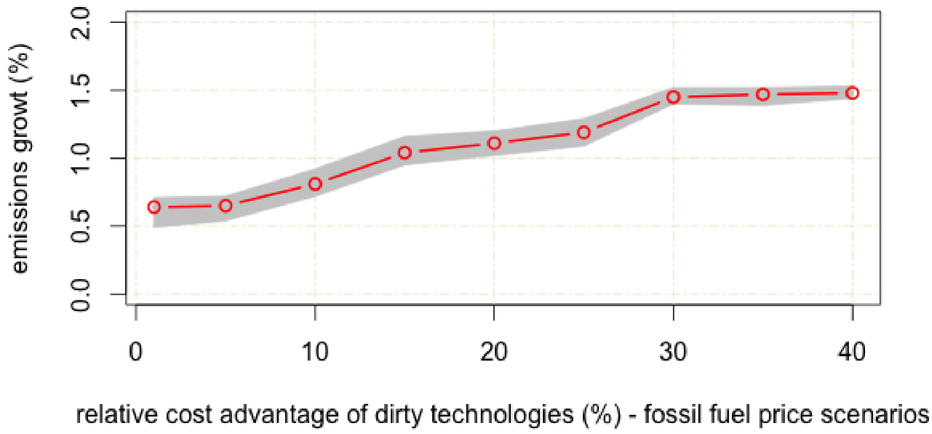
Figure 6: Likelihood of transition, output growth and emissions growth under individual labour productivity (LP) climate damages. MC of size 200, shaded area represents 95% confidence interval.



(a) Likelihood of transition.

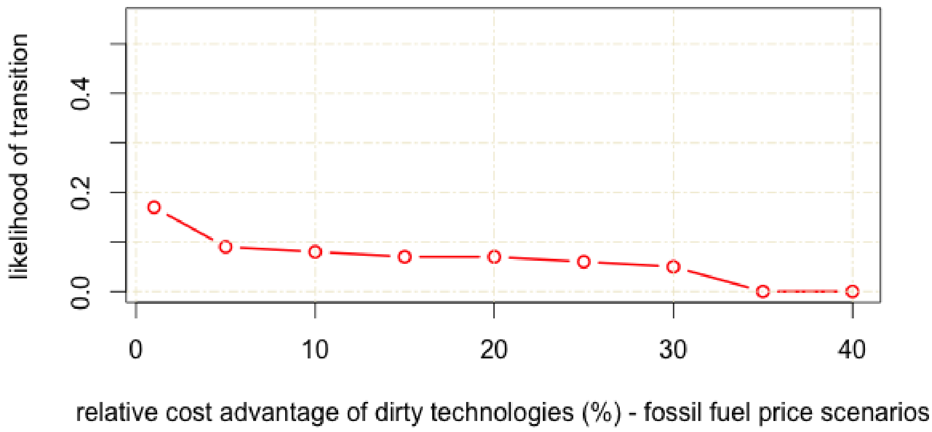


(b) GDP growth.

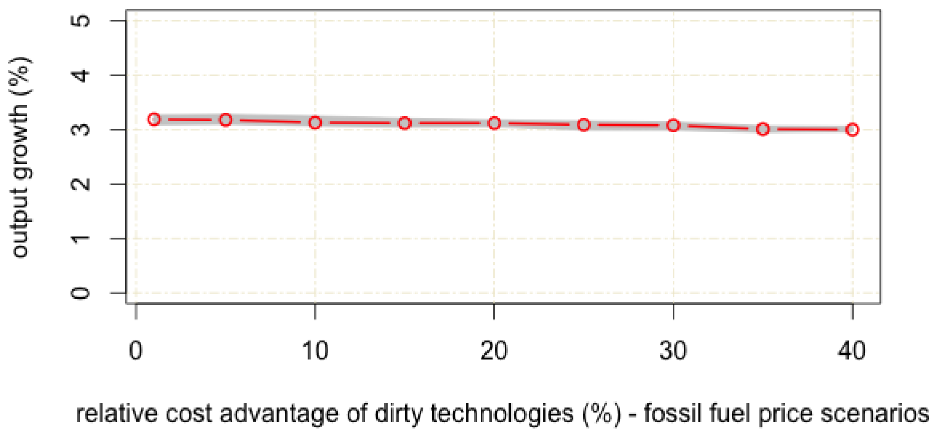


(c) Emissions growth.

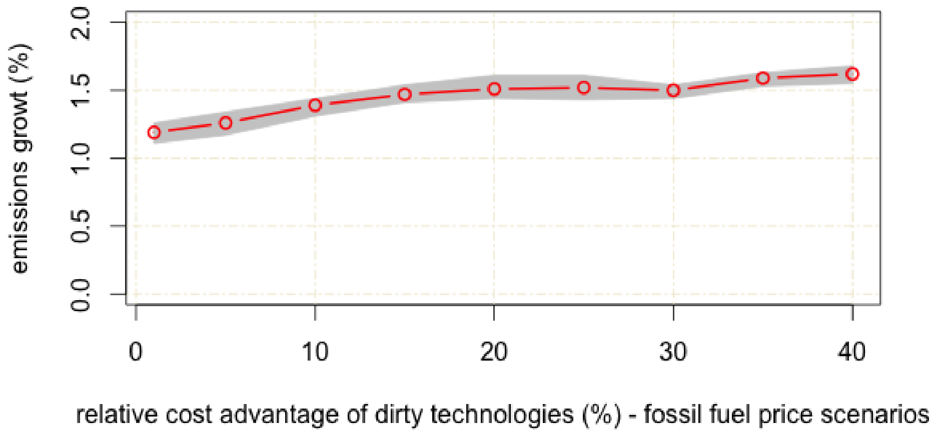
Figure 7: Likelihood of transition, output growth and emissions growth under individual energy efficiency (EE) climate damages. MC of size 200, shaded area represents 95% confidence interval.



(a) Likelihood of transition.



(b) GDP growth.



(c) Emissions growth.

Endogenous Growth in Production Networks[‡]

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January 15, 2017

Abstract

We investigate the interplay between technological change and macro-economic dynamics in an agent-based model of the formation of production networks. On the one hand, production networks form the structure that determines economic dynamics in the short run. On the other hand, their evolution reflects the long-term impacts of competition and innovation on the economy. We account for process innovation via increasing variety in the input mix and hence increasing connectivity in the network. In turn, product innovation induces a direct growth of the firm's productivity and the potential destruction of links. The interplay between both processes generate complex technological dynamics in which phases of process and product innovation successively dominate. The model reproduces a wealth of stylized facts about industrial dynamics and technological progress, in particular the persistence of heterogeneity among firms and Wright's law for the growth of productivity within a technological paradigm. We illustrate the potential of the model for the analysis of industrial policy via a preliminary set of policy experiments in which we investigate the impact on innovators' success of feed-in tariffs and of priority market access.

1 Introduction

In contrast with the extremely detailed description of markets and financial interactions that have been developed in the recent literature [see e.g Dawid et al., 2014, Dosi et al., 2015, and references below], the representation of the innovation process has remained relatively stylized in agent-based macro-economic models. It is usually assumed that technological progress materializes at the micro level through (exponential) growth in the productivity of capital goods over time. Hence the models abstract away from the micro-economics of technological change and fail to inscribe technological processes in the economic state space.

[‡]The authors gratefully acknowldege the support of the EU FP7 project IMPRESSIONS

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This strongly contrasts with the detailed analysis of the innovation process that has been developed in the evolutionary literature [see Dosi and Nelson, 2010, for a recent survey]. More importantly, this leaves an important gap open in terms of policy analysis. Indeed, without a detailed representation of innovation and technological processes, agent-based models can hardly be used to analyze policies that involve large impacts on technologies, first and foremost climate change mitigation, which possibly is the most important long-term challenge faced by contemporary economies. Indeed, the direction of technological change and the specific nature of inputs entering the production process are key elements for an assessment of technological change from the point of view of climate policy.

In order to fill part of this gap, we introduce in this paper an agent-based model where technological evolution is modeled in details through the evolution of production networks. These networks provide a detailed description of the technological and commercial relationships between firms and can easily be mapped to an input-output table. On the one hand, they form the structure that determines economic dynamics in the short run. On the other hand, their evolution reflects the long-term impacts of competition and innovation on the economy.

Accordingly, in our model, once the network is given the dynamics of prices and output follow from the application of simple behavioral rules. Conversely, the evolution of the network reflects the long-term dynamics of the economy driven by competition and innovation processes. Competition materializes via redirections (rewiring) of relationships between firms and hence induce an "horizontal" evolution of the network. Innovation and technological change, which form the core of our model, materialize both via radical (product) innovation and incremental (process) innovation. Radical innovation occurs through the discovery by firms of new technological paradigms that lead to increasingly efficient products. Process innovation materializes, within a technological paradigm, through diversification of the input mix. The interplay between these processes drives the evolution of the network: process innovation through diversification leads to increasing connectivity among firms while radical innovations might render obsolete a very mature technology and hence induce a decrease in connectivity. The input-output structure of the model evolves accordingly. We hence approach what is according to [Dosi and Nelson, 2010] *a quite challenging modeling frontier [that] regards the explicit representation of evolving problem-solving procedures, constrained by paradigm-shaped 'grammars' and their ensuing dynamics in the more familiar space of input/output coefficients.*

The model is able to reproduce key stylized facts of industrial dynamics with respect to the distribution of firms' growth rates and size, the persistence of heterogeneity in productivity among firms or the structure of production networks. Also, our representation of process/incremental innovation is consistent with Wright's law [Wright, 1936]. When combined with radical innovation and imitation à la Nelson and Winter (1982), it leads to the emergence of endogenous growth paths and of technology-driven business cycles. These cycles are characterized by the transition between phases of radical/product and incremental/process innovation akin to the one described in the Utterback-Abernathy model [see Utterback, 1994]. In summary, the model is able to reproduce a rich set of stylized facts and provide bridges between innovation and endogenous growth theories.

Hence, we provide an agent-based framework fit for the analysis of large technological changes in the economy and potentially of innovation policies. In this latter respect, we perform a first series of policy experiments in which we investigate the impacts of price-based measures, akin to feed-in tariffs, and quantity-based measures, i.e preferential access to the market, on the survival rate of radical innovators and the growth rate of the economy. Our results emphasize that the impacts of such policy measures heavily depend on the strucuture of externalities in the innovation process.

The remaining of the paper is organized as follows. In section 2, we review the related literature. Section 3 gives a detailed description of the model. Section 4 investigates the impact of different innovation process on the structure of the production network and on macro-economic dynamics. Section 5, highlights the behavior of the model in a series of policy experiments and section 6 concludes.

2 Related Literature

In most existing agent-based macro-economic models, the representation of the production process is rather stylized and involves only labor and capital, possibly of heterogeneous kinds. Intermediary consumption or the details of the "recipes" used in production are usually not accounted for. Accordingly, technological progress is embedded in physical capital whose vintages grow in productivity over time. This approach is rather generic and followed in particular in [Dosi et al., 2010, 2013, 2015], [Dawid et al., 2011, 2014] or Ciarli et al. [2010]. Mandel et al. [2010] and Wolf et al. [2013] uses a different representation of the production process that accounts for intermediary consumption but productivity growth is driven by cumulative investment and hence totally decoupled from the specifics of the production process.

In contrast, in our setting, growth in productivity is essentially linked to changes in the production process and correlatively in the production network. Hence our approach is closely related to the evolutionary and complex systems literature that have focused on the dynamics of technology. This literature is extensively surveyed in [Frenken, 2006b] and [Dosi and Nelson, 2010]. In particular [Frenken, 2006b] identifies three main approaches in the literature: fitness landscape models [e.g Kauffman et al., 2000], percolation models [e.g Silverberg and Verspagen, 2005], and production recipes models [e.g Auerswald et al., 2000]. The most relevant contributions from our perspective are those that model the evolution of "production recipes" such as [Auerswald et al., 2000], Frenken [2006a] and more recently [McNerney et al., 2011]. These contributions are strongly rooted in an engineering/design perspective and, following Kauffman [1993], emphasize the interdependencies among the elements of designs as the key parameter determining the dynamics of technologies. In particular, [McNerney et al., 2011] emphasizes that the interplay between complexity of the design, measured via the degree of interdependency, and the increasing difficulty in improving components leads to the emergence of Wright's law for the rate of technological progress [see Wright, 1936, Arrow, 1962, in this latter respect]. Our approach is slightly more aggregate and distant from engineering considerations as we map the technological process directly in the input-output space. This allows us to provide the macro-economic closure that misses in the "production recipes" contributions. With respect to Wright's law, we obtain results similar to those of [McNerney et al., 2011].

We go beyond process innovation through the introduction of radical innovation, which leads to the discovery of new technological paradigms and growth in products' productivity. In our micro-founded setting, combining product and process innovation is required to induce exponential growth. This provides an interesting contrast with standard approaches in the endogenous growth literature. Except in degenerate case [see d'Autume and Michel, 1993], growth models à la Arrow [1962] based on Wright's law are not conductive to exponential growth. Hence endogenous growth models à la Romer [1990] requires the variety of inputs in the production process to grow exponentially in order to generate sustained growth. This assumption might appear as innocuous when the production process is represented at the aggregate level but leads to major inconsistencies with empirical regularities if implemented in our micro-economic setting. Hence, the emergence of exponential growth requires more radical forms of product innovation of the kind considered in "Schumpeterian" growth models à la Aghion and Howitt [1992]. Whereas, this "schumpeterian" literature considers that the growth process is driven by a succession of monopolies, in our setting different technological "paradigms" at different levels of maturity and diversification co-exist. This allows to preserve competition and heterogeneity in productivity among firms, consistently with empirical observations.

The hybrid nature of our model echoes the considerations about variety put forward in [Saviotti et al., 1996], in particular Saviotti's second hypothesis according to which *Variety growth, leading to new sectors, and productivity growth in pre-existing sectors are complementary and not independent aspects of economic development.* More broadly, we could argue that we operationalize, via a network-based approach, Saviotti and Pyka [2008]'s concept of variety, which is broader than this of product variety since it refers to the extent of diversification in the economic system.

Finally, our network perspective on the productive system relates to an expanding stream of literature using both agent-based [Bak et al., 1987, Weisbuch and Battiston, 2007, Battiston et al., 2007] and general equilibrium methods [Acemoglu et al., 2012, Carvalho, 2014]. This literature hasn't yet approached the issue of growth and technological change but for the notable exception of Carvalho and Voigtländer [2014]. These authors put forward a new stylized fact at both the sector and the firm level: *producers are more likely to adopt inputs that are already used – directly or indirectly – by their current suppliers.* They provide theoretical foundations for this process using the network formation model of Jackson and Rogers [2007], which they adapt by considering that new products/firms entering the economy draw a first part of their inputs at random and a second part from the connections of these drawn in the first phase. Hence their approach is much more precise than ours with respect to the direction of technological change. Yet, our approach is complementary to theirs as it allows the macro-economic closure of the model and account for the interplay between product and process innovations.

3 The model

3.1 Technological structure

We represent the dynamics of a network consisting of (at most) m firms distributed over S industrial sectors and one aggregate household. We denote the set of firms by $M = \{1, \cdots, m\}$, the household by the index 0 and the set of agents by $N = \{0, \cdots, m\}$.Time is discrete, indexed by $t \in \mathbb{N}$. The network of supply relationships is represented by an adjacency matrix A^t such that $a^t_{i,j} = 1$ if and only if j is a supplier of i (and $a^t_{i,j} = 0$ otherwise). The network evolves over time under the influence of competition and innovation.

Production processes are linked to the structure of the network via production functions, which are assumed to be of the C.E.S type as in the literature on monopolistic competition on the intermediate goods markets (see Ethier [1982], Romer [1990]) . More precisely, given a production network A, the set of suppliers of firm i is $\Sigma_i(A) := \{j \in M \mid a_{i,j} = 1\}$ and its production possibilities are given by the function:

$$f_i^t(x_0, (x_j)_{j\in\Sigma_i(A)}) := x_0^\gamma\Big(\sum_{j\in\Sigma_i(A)} (e_j^t x_j)^\theta\Big)^{(1-\gamma)/\theta} \tag{1}$$

where $\gamma \in (0, 1)$ is the (nominal) share of labor in the input mix, $1/(1-\theta)$ is the elasticity of substitution, $x_0 \in \mathbb{R}_+$ is the quantity of labor and x_j the quantity of input j used in the production process, and e_j the productivity of input j.

Technological progress and the evolution of the network will then be closely intertwined. In particular, we shall assume throughout the paper that inputs are substitutable (i.e $\theta \in [0, 1]$), and hence productivity will grow with the number of inputs/suppliers combined, that is with the density of the network. As a matter of fact, our results rely on the presence of increasing returns to variety rather than in the choice of a specific functional form for the production function or even the existence, at all, of a production function.

3.2 Macro-economic closure

We also attach the evolution of the economy to this of the network. Therefore, we follow Gualdi and Mandel [2015] and consider that the structure of the network determines the dynamics of the economy according to a set of behavioral rules. More precisely, let us denote by A^t the adjacency structure of the network in period t and let for every agent i, denote by $w_i^t \in \mathbb{R}_+$ the wealth it holds, $q_i^t \in \mathbb{R}_+$ the stock of output it has produced, $p_i^t \in \mathbb{R}_+$ the price it sets for its output, and $(\alpha_j^t)_{j \in \Sigma_i(A^t)} \in \mathbb{R}_+^{\Sigma_i(A^t)}$ the input shares it chooses. The dynamics of the economy during period t are then completely determined by the structure of the network. More precisely, the following sequence of events take place during a period:

1. Agents receive a nominal demand proportional to the wealths and the input shares of their connections.
2. Agents adjust their prices toward their market clearing value (at a rate $\tau_p \in [0, 1]$).
3. Agents then produce according to the inputs they receive.
4. Agents adjust their input shares (at a rate $\tau_w \in [0, 1]$) towards their cost-minimizing value.

A detailed representation of these dynamics is given in the appendix A.2. One of their salient property is that, if the network is fixed, the economy almost generically converges to the underlying general equilibrium [see Gualdi and Mandel, 2015].

3.3 Network Dynamics

Now, our key focus in this paper is the joint evolution of the production network and of the economy. That is, the evolution of the adjacency structure $(A^t)^{t \in \mathbb{N}}$ over time and its impact on macro-economic dynamics. We shall consider two main drivers for this evolution: competition and innovation.

Competition materializes through the possibility for firms to periodically shift part of their business to more competitive suppliers. More precisely, we consider that at the end of each period, each firm independently receives the opportunity to change one of its suppliers with probability $\rho_{chg} \in [0, 1]$. If this opportunity materializes for firm i in period t, it selects randomly one of its suppliers $\bar{j}_i$ (in sector $S_{\bar{j}_i}$) and another random firm j (in the same sector) among those to which it is not already connected. It then shifts its connection from firm $\bar{j}_i$ to firm j if and only if the price (normalized per unit of productivity) of j is less than the one of $\bar{j}_i$. In other words, the adjacency matrix A^t evolves according to:

$$a_{i,\bar{j}_i}^{t+1} = \begin{cases} 1 & \text{if } \dfrac{p_{\bar{j}_i}^t}{e_{\bar{j}_i}} \leq \dfrac{p_j^t}{e_j} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$a_{i,j}^{t+1} = 1 - a_{i,\bar{j}_i}^{t+1}$$

The actual weight of the new connection is then determined according to an average over other suppliers' weights.

This competitive process leads to the evolution of the in-degree distribution of the network. In fact, as shown in Gualdi and Mandel [2015], competition leads to the emergence of a scale-free in-degree distribution because of two basic facts about the "economy" of suppliers' switches. On the one hand, the number of incoming business opportunities for a firm is independent of its size, i.e. firms gain link at a constant rate. On the other hand, the rate at which existing consumers may quit grows linearly with the size of the firm, i.e firms lose links proportionally to their degree. The balance between the flow of incoming and outgoing links lead to the emergence of a scale-free size distribution of incoming links.

Remark 1 *The rewiring process described by Equation 2 also implicitly defines the notion of sector in our setting. A sector is a group of firms whose outputs are substitutable (from the point of view of the clients). Hence, despite our use of a C.E.S functional form, the substitutability between inputs is actually limited by the sectoral structure of the economy. Further note that the outputs from the different firms of a sector, though substitutable, are not equivalent as their productivity/quality might differ.*

Innovation materializes through two processes that account respectively for product and process innovation (and in an extended sense for radical and incremental innovation). More precisely, two element characterize a technology in our setting, the productivity $e \in \mathbb{R}_+$ of the product produced and the input mix $\upsilon \in \mathbb{N}^S$, i.e the number of inputs from the different sectors used in the production process. In turn, a technological paradigm consists in a pair $(e, \Upsilon) \in \mathbb{R}_+ \times 2^{\mathbb{N}^S}$ where e represents the productivity of the product produced and Υ the set of input mixes that can be used to produce the product. In general, we shall assume that Υ is of the form $\Upsilon := \{\upsilon \in \mathbb{N}^{S_\Upsilon} \mid S_\Upsilon \subset S \wedge \upsilon \leq \overline{\upsilon}\}$ where $\overline{\upsilon}$ represents the most complex (and hence productive) input mix within the paradigm. That is the production process can gain in efficiency through diversification up to a maximum amount of diversification, which is technology specific.

Let us consider a firm i is that is using a technology (e_i, υ_i) within a paradigm (e_i, Υ_i). An incremental innovation for that firm consists in the adoption of a new input mix $\tilde{\upsilon}_i$ within the paradigm (e_i, Υ_i) such that $\tilde{\upsilon}_i \geq \upsilon_i$. A radical innovation consists in the adoption of a new technological paradigm $(\tilde{e}_i, \tilde{\Upsilon}_i)$ such that $\tilde{e}_i \geq e_i$ and of an input mix $\tilde{\upsilon}$ within the new paradigm. Our approach hence builds on Dosi [1982] interpretation of the determinants and direction of technological change.

Changes in the input mix materialize through the addition or the deletion of links. Hence, innovation is embedded within the network and technological progress materializes through the evolution of the network. As for the drivers of technological progress, we consider three possible avenues for productivity growth: process/incremental innovation, product/radical innovation and imitation as in the evolutionary model of Nelson and Winter(1982). More precisely each firm i invests a fixed share θ of its revenues in R and D and this yields with probability ρ_{inn} per period an innovation, i.e every period, a share ρ_{inn} of firms are selected uniformly at random to draw an innovation. This innovation can be of three types: incremental, radical or imitative. More precisely, one has:

- With probability μ_{inc} an incremental innovation is drawn, in which case a new supplier is drawn at random and added to the input mix (if the current number of suppliers is less than the maximum possible within the paradigm).
- With probability μ_{rad} a radical innovation, in which case a new technological paradigm $(e_i^{t+1}, \Upsilon_i^{t+1})$ is drawn at random. The input mix υ_i^{t+1} then is reinitialized by drawing the new number of links according to a binomial distribution whose mean equals the mean number of links in the initial network, υ_0. The maximal number of links for the new paradigm is itself drawn uniformly between $\upsilon_{\min}$ and $\upsilon_{\max}$, which are parameters of the model.
- With probability μ_{im} the firm imitates one of its peers[1]. That is, it observes a firm i' at random and adopts its technology $(e_{i'}, \upsilon_{i'})$ if it is more advanced than its current one in the sense that its more productive $e_{i'} > e_i$.
- The network is then updated accordingly. That is if the firm has extended its input mix the corresponding number of new suppliers is drawn at random (and the corresponding entries are added to the adjacency matrix). If the firm has adopted a new technological paradigm but with a less elaborate input mix, the corresponding number of links (and the corresponding entries of the adjacency matrix) are selected uniformly at random and deleted.
- As a result of this process and of competition, some firms might lose incoming connections, consumers, up to the point where they no longer have any connection in the network. We consider that such a firm goes bankrupt and exits the market. Yet, to sustain competition in the economy, we assume that those exits are compensated by entries of new firms. New firms enter the market with a productivity equal to the average in the economy and with a number of suppliers drawn from a binomial distribution as in Gualdi and Mandel [2015].

These different mechanisms can be seen as micro-economic implementations of the macro-economic drivers of growth considered in the endogenous growth literature. On the one hand, the incremental/process innovation, which consists in adding inputs to the production process is very similar to the product variety model of endogenous growth à la Romer [1990], as well as to the inframarginal approach to economic growth [see Yang and Borland, 1991] or of Adam

[1] Here and in the following, we always consider implicitly that the vector $(\mu_{inc}, \mu_{im}, \mu_{rad})$ is normalized so that $\mu_{rad} + \mu_{inc} + \mu_{im} = 1$

Smith's original description of the effects of the division of labor. A number of empirical contributions have also documented the positive impact of increasing input variety on productivity growth: through trade-based measures of variety in Addison [2003], Feenstra et al. [1999], Funke and Ruhwedel [2001] as well as through direct measures of the variety of inputs used in the production process in the more recent contributions of Amiti and Konings [2007] and Frensch and Wittich [2009].

On the other hand, the product innovation process, which leads to a change of technological paradigm and to a direct increase of productivity implements a more radical form of innovation. It has strong similarities with Schumpeterian models of endogenous growth in which series of monopolists sequentially push each other out of the market by developing more productive versions of a product (see Aghion and Howitt [1998] and references therein for an extensive description of the "Schumpeterian" approach to endogenous growth as well as Aghion et al. [2013] for a recent review of empirical evidences on the Schumpeterian growth engine).

We investigate in the following the macro-economic and distributional patterns that emerge from the interplay of these processes.

4 Innovation, growth and the evolution of production networks

Our first objective is to characterize the impact of the different innovation processes under consideration on the macro-economic dynamics and the structural properties of the production network. Therefore, we perform series of monte-carlo experiments under varying innovation regimes: incremental only, radical only, incremental and radical in combination. Building on the sensitivity analysis developed in Gualdi and Mandel [2015], we use as default in these experiments the set of parameters given in table 1, which are representative of the behavior the model in absence of innovation. Unless otherwise specified, we run simulation with fifty different random seeds for each parameter combination in order to average out stochasticity. However, we observe very little variability or macro-economic dynamics with varying seeds : for all the results reported below about output and number of links, the standard error is below 1%. Therefore, we report only the results of a single simulation per set of parameters.

Parameter	Value
m	2000
S	5
T	500 000
ρ_{chg}	0.05
τ_p	0.8
τ_w	0.8
ρ_{inn}	0.001
θ	1/2
$\upsilon_{\min}$	10
$\upsilon_{\max}$	20
υ_0	4

Table 1: Default parameter values

Also note that if the speed of innovation becomes too large with respect to this of price and quantity adjustment, the economy can't cope with technological change and the system becomes unstable. In other words, the time-scales at which technological innovation on the one hand and price and quantity adjustment on the other hand take place must somehow be separated. In our setting, this implies considering relatively low rates of innovation (of the order of 10^{-3} or 10^{-4}). Two other mechanisms tend to slow down the diffusion of innovation. On the one hand, not all innovations are successful: because of the disruption it induces in the organisation of the firm, innovation might initially make the firm less competitive and possibly lead it to failure. On the other hand, there is a lag between the success of a radical/incremental innovation within a firm and its diffusion through imitation in the economy as in Fagiolo and Dosi [2003]. Indeed each imitation is by itself an innovation for the imitating firm and such an event occurs independently for each firm (and at a relatively low innovation rate). This set of mechanisms imply that in the simulations presented below, a relatively large number of periods is required for a statistical equilibrium to emerge.

4.1 Incremental Innovation

We first focus on the dynamics of the model when the technological paradigm (i.e the maximal number of inputs) is fixed and only incremental innovation occurs, i.e the only source of productivity growth is the diversification of the input mix. In this setting, we perform a series of monte-carlo simulations focusing on the sensitivity of the model with respect to the rate of innovation and the elasticity of substitution. More precisely, we let ρ_{inn} vary in $\{10^{-2}, 5.10^{-3}, 10^{-3}, 5.10^{-4}, 10^{-4}\}$ and θ vary in $\{3/5, 1/2, 1/4\}$. The technological paradigm for each firm is such that $e_i = 1$ and $\overline{\upsilon}_i = 20$.

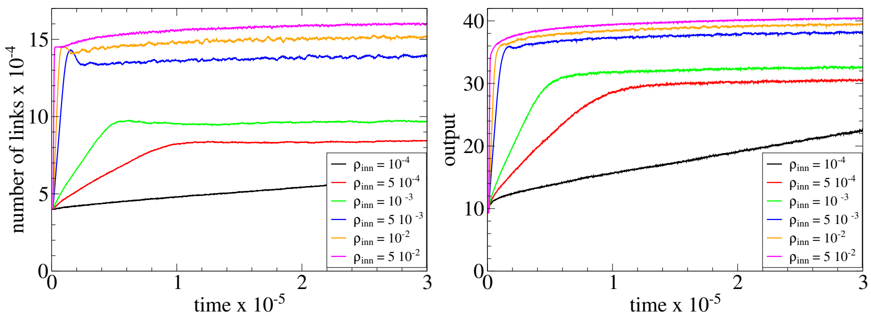

Figure 1: Evolution of the number of links (left) and of total output (right, log scale) for representative simulations corresponding to a 100% rate of incremental innovation, with varying innovation rates. Other parameters are set as in table 1.

The results of simulations, illustrated in figure 1, show that the qualitative behavior of the model is independent of the choice of parameters. In a setting where innovation ocurrs only within a fixed technological paradigm, increasing product variety is a transitory process: it lasts until the frontier of the technological paradigm is reached and connectivity saturates. In absence of saturation, the growth of the number of inputs ought to be linear as the number of inputs (tentatively) added to the production process is constant over time. However, the actual pattern is sublinear (see left panel of figure 1) given that the rate of success of these incremental innovations decreases as more firms approach the frontier of the technological paradigm. Two complementary mechanisms are at play in this process. On the one hand, firms that have reached the frontier of the technological paradigm can no longer seize innovation opportunities so that the number of firms that benefit from incremental innovation decreases over time. On the other hand, as $\theta < 1$, the marginal returns to incremental innovation are decreasing and hence the probability of success of an incremental innovation decreases with connectivity. The right-panel of figure 1 presents the macro-economic counterpart of this connectivity pattern. Output grows at a decreasing rate during a transitory regime and then stabilizes.

It is clear that linear (or sublinear) increase in product variety can not lead to exponential growth, even if one abstracts away from the saturation process. In order to provide a quantitative approximation of the transient growth regime, we use the simplifying assumption that each input is used in similar quantity in the production process and has a normalized productivity of 1. The quantity of output obtained by using $1/n$ units of n distinct varieties of inputs (and of a quantity of labor normalized to unity) is then given by:

$$f(1, 1/n, \cdots, 1/n) = \left(n(1/n)^{\theta}\right)^{(1-\gamma)/\theta} = n^{(1/\theta - 1)(1-\gamma)} \quad (3)$$

Thus, if one discards the saturation process and considers that the number of inputs grows linearly over time, i.e $n(t) = kt$, productivity (and production) shall grow as

$$\phi(t) = (kt)^{(1/\theta - 1)(1-\gamma)} \tag{4}$$

consistently with Wright's law which, in its original form [see Wright, 1936] states that production cost decreases (or productivity increases) as a power law of cumulative production [see also Arrow, 1962, McNerney et al., 2011]. In order to test the validity of this approximation in our framework, we have estimated the time dependency of output in the simulated data (before the establishment of the stationary regime) using a model of the form

$$y = (at)^b \tag{5}$$

and compared the estimated b exponent with the one predicted by equation 4. Table 2 illustrates our results. Equation 5 fits remarkably well the simulated data and the value of the estimated exponent is consistent with the one put forward in equation 4, with a downward bias that can be explained by the progressive saturation process.

Table 2: Wright law exponent for varying elasticity

	Dependent variable: $\log(y)$		
	$(\theta = 3/5)$	$(\theta = 1/2)$	$(\theta = 1/4)$
$\log(t)$	0.207^{***}	0.321^{***}	1.002^{***}
	(0.0001)	(0.0002)	(0.001)
Constant	-0.306^{***}	-0.143^{***}	0.776^{***}
	(0.001)	(0.002)	(0.006)
Observations	99,001	99,001	99,001
R^2	0.965	0.965	0.966
Adjusted R^2	0.965	0.965	0.966
Residual Std. Error (df = 98999)	0.035	0.054	0.165
Note:			*p<0.1; **p<0.05; ***p<0.01

Hence, the incremental innovation process introduced in the model leads to a behavior which is consistent with the empirical evidence on the growth of productivity within a technological paradigm, which is summarized by Wright's law. Empirical estimates of Wright's law suggest an exponent close to $1/3$, corresponding to a value of θ of $3/5$ in our framework.

Another stylized fact of industrial dynamics that the model closely matches is that the degree distribution of firms' size, measured via their number of incoming connections, is scale free (see the left panel of Figure 2 and the related discussion in Gualdi and Mandel [2015]).

From a theoretical perspective, the incremental innovation process considered in this section is closely related to the product variety models à la Romer

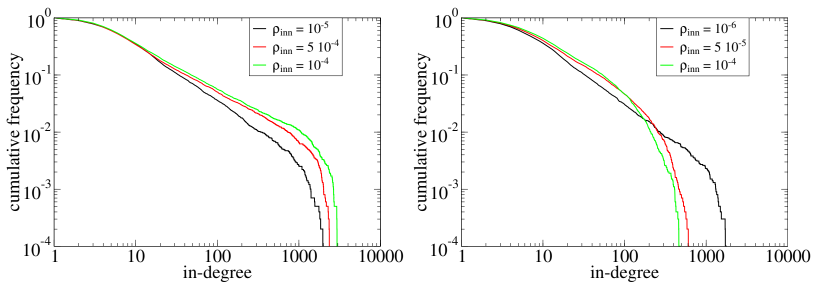

Figure 2: Distribution of in-degrees after 2.10^6 periods for varying innovation rates. Left panel corresponds to incremental innovation only (subsection 4.1), right panel to radical innovation only (subsection 4.2). Other parameters are set as in table 1.

[1990]. However, in our setting, diversification is embedded at the core of the production process whereas in Romer's type of model the production process is represented in a much more aggregate way and diversification only concerns the production of a final good. From Romer's aggregate perspective, the assumption that product variety grows exponentially over time, which is required to sustain endogenous growth, does not seem overly problematic. In our micro-founded setting, exponential growth of product variety would imply either exponential growth of the network's density or of the number of firms. Both assumptions clearly are counter-factual. Hence, incremental innovation alone can not sustain endogenous growth except in the corner case where there is infinite complementary between inputs ($\theta \to 0$) and the exponent of Wright's law $\beta = (1/\theta - 1)(1-\gamma)$ tends towards infinity [as in d'Autume and Michel, 1993].

4.2 Radical Innovation

In a second series of experiments, we focus on the effects of radical innovation on industrial and macro-economic dynamics. Radical innovation yields a direct increase in productivity through product innovation. In this respect, it has similarities with Schumpeterian models of endogenous growth [see Aghion and Howitt, 1998, and references therein] in which series of monopolists sequentially push each other out of the market by developing more productive versions of a product hence putting the economy on an exponential growth path.

In order to characterize the impact of radical/product innovation in our setting, we perform a series of monte-carlo simulations in which it is the only source of innovation (i.e we set $\mu_{rad} = 1$ while $\mu_{inc} = \mu_{im} = 0$) and the total innovation rate ρ_{inn} varies in $\{10^{-2}, 5.10^{-3}, 10^{-3}, 5.10^{-4}, 10^{-4}\}$.

The results of the simulations show that, from the macro-economic perspective, the qualitative behavior of the model is independent of the innovation rate. As illustrated in figure 3, radical innovation systematically leads to exponential growth. The growth regime establishes itself rapidly and is remarkably stable. Moreover, in absence of radical innovation, the average connectivity and the outdegree distribution of the network are also stable. The only source of volatility appears to be the entry and exit process of firms.

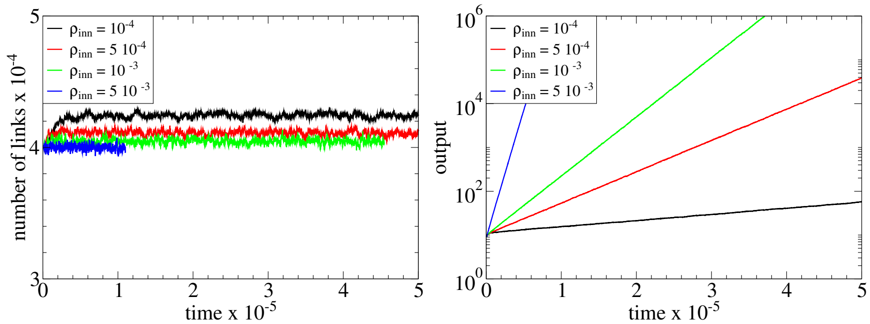

Figure 3: Evolution of the number of links (left) and of total output (right, log scale) for representative simulations corresponding to a 100% rate of radical innovation, with varying innovation rates. Other parameters are set as in table 1. Note that on the right panel, simulations corresponding to $\rho_{inn} = 10^{-3}, 5 \cdot 10^{-3}$ leave the panel box because growth is too rapid.

The impact of changes in the innovation rate materialize first by changes in the growth rate of the economy (see figure 3). From a more structural perspective, large innovation rates increase volatility in the growth patterns of firms. This materializes in the indegree distribution of firms. While the distribution is scale-free in presence of incremental innovation only, the presence of radical innovation affects the stability of large firms and shifts the distribution towards exponential tails for large value of the innovation rate ρ_{inn}(see right-panel of figure 2). This feature can be explained by the fact that the strength of competition increases with the speed at which new products, radical innovations, enter the market. Hence, the negative feedback effects on the growth of firms are much more important leading to the decrease of the tail of the distributions of sizes. This feature of the model might help clarify why conflicting evidences remain about the size distribution of firms (see e.g Cabral and Mata [2003] and Axtell [2001]). Shifts between different type of distributions might well depend on the growth pattern of the economy.

In all cases, heterogeneity between firms is an emerging property of the model that is in strong contrast with the monopolistic feature of growth models à la Aghion and Howitt [1998] and brings the model much closer to empirical stylized facts about industrial dynamics. In the following, we investigate in more details how, through the interplay between incremental and radical innovations, the model can also account for complex dynamical patterns of output.

4.3 Mixed innovation regimes and complex dynamics

The experiments performed in the preceding subsections underline the complementary roles of incremental and radical innovations. Incremental innovation accounts for technological progress within a technological paradigm but saturates once the technological frontier is reached. Radical innovation accounts for the development of new products and paradigms and allows to sustain endogenous growth.

In this section, we investigate the interplay between these processes and in particular the impact on macro-economic and industrial dynamics of the competition between radical innovators and incumbents. This competition hardly materializes in presence of radical innovation only because all firms, incumbents and innovators, then have the same expected product variety υ_0 (see subsection 3.3) and hence innovators always have a competitive advantage thanks to the increased productivity of their product. When both radical and incremental innovation are present, radical innovators, which initially have a low level of diversification/complexity (υ_0 in expectation), have to compete with incumbents that have climbed the complexity ladder with an older vintage of the product.

In order to investigate the impact of this competition, we have performed a series of experiments in which the ratio ${}^{\mu_{inc}}/_{\mu_{rad}}$ between the rates of incremental and radical innovation varies in $\{[1, 5, 10, 20, 50]\}$. Other parameters are set as in table 1 and there is no imitation (i.e $\mu_{im} = 0$).

The results of the simulations show first that exponential growth is a very robust property of the dynamics: provided the rate of radical innovation is positive, the model eventually settles in an exponential growth regime after a transient period (see figure 4). The growth rate is an increasing function of the total innovation rate and a decreasing function of the ratio between incremental and radical innovation, i.e it increases with the rate of radical innovation. Conversely, the length of the transient decreases with the total innovation rate and increases with the ratio between incremental and radical innovation. In fact, a key parameter for the dynamics seems to be the expected frequency of radical innovations, which is proportional to $\rho_{inn} \times {}^{\mu_{rad}}/_{\mu_{inc}}$.

During the transient period, the dynamics of output and of connectivity, illustrated in figure 4 , are very similar to those observed in presence of incremental innovation only (see section 4.1): the growth of output is driven by the increasing product variety in the production process (or equivalently by the increasing connectivity in the network). The growth pattern is also consistent with Wright's law. The transition to the stable regime occurs smoothly when the growth rate has reached an "equilibrium" value, which depends on the frequency of radical innovations. The end of the transient regime is also marked by the stabilization of connectivity. This "equilibrium" level of connectivity does not in general saturate the constraint of the technological paradigms (maximal number of suppliers) and decreases with the frequency of radical innovation (see figure 4). It is independent of the elasticity of substitution and of the maximal number of links.

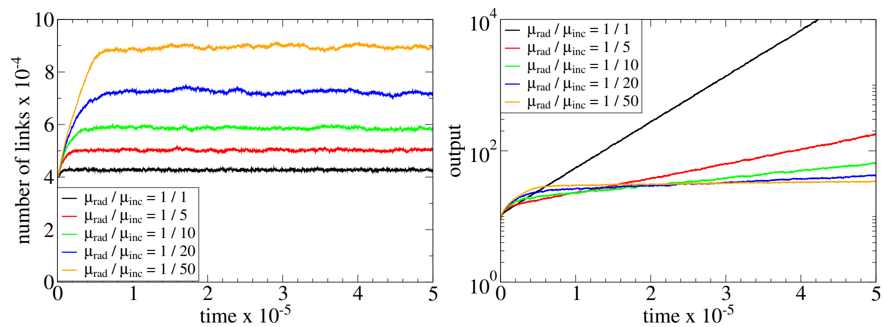

Figure 4: Evolution of the number of links (left) and of total output (right, log scale) for representative simulations with varying ratios between the rates of incremental and radical innovation (upper panel) and varying level of innovation rates (lower panel). Other parameters are set as in table 1

In fact, the equilibrium level of connectivity (or equivalently of product variety) is determined by the interplay between radical and product innovation. On the one hand, the frequency of incremental innovations determines a rate of increase of the number of links. On the other hand, radical innovations, if successful, lead to a decrease of the number of links. The frequency of success of radical innovations hence determine a rate of decrease of the number of links. The equilibrium level of connectivity corresponds to a level that balance creation and destruction of links. The larger the ratio between incremental and radical innovations, the higher this equilibrium level.

The dynamics of connectivity can then be explained by the presence of decreasing returns to connectivity/product variety (i.e $\theta > 0$). During the transient period, while connectivity is lower than the equilibrium threshold, productivity gains induced by incremental innovation are large and can not be disrupted by radical innovations. While most firms' technologies are below this threshold, the increase in product variety is almost unconstrained. In the stable regime, returns to incremental innovation are lower, the model is at an equilibrium where productivity gains (per unit of time) induced by radical innovations are competitive with these induced by incremental innovations. Hence, the increase in connectivity due to incremental innovations is compensated by the decrease triggered by radical innovations.

With a large number of incremental and radical innovations, these mechanisms are only observed indirectly through the stability of the average level of connectivity. In order to characterize them more precisely, we focus on a more stylized version of the model where radical innovation is rare but gets amplified through imitation. Therefore, we run a second series of monte-carlo simulations in which innovation by imitation is enabled. We let the ratio between incremental and radical innovation,${}^{\mu_{im}}/_{\mu_{rad}}$, vary in $\{10, 20, 50\}$. We also let the ratio ${}^{\mu_{inc}}/_{\mu_{rad}}$ vary in $\{1, 10, 20\}$ and set other parameters as in table 1.

Our analysis mainly focuses on the properties of the stable regime, which is still characterized by exponential growth in the long-run. Yet, a key feature that emerges is the presence of technologically driven-business cycles, which materialize via fluctuations of the output and of the connectivity in the network, i.e of the average product variety of the technologies used (see figure 5, in particiular upper-left and lower-right panels).

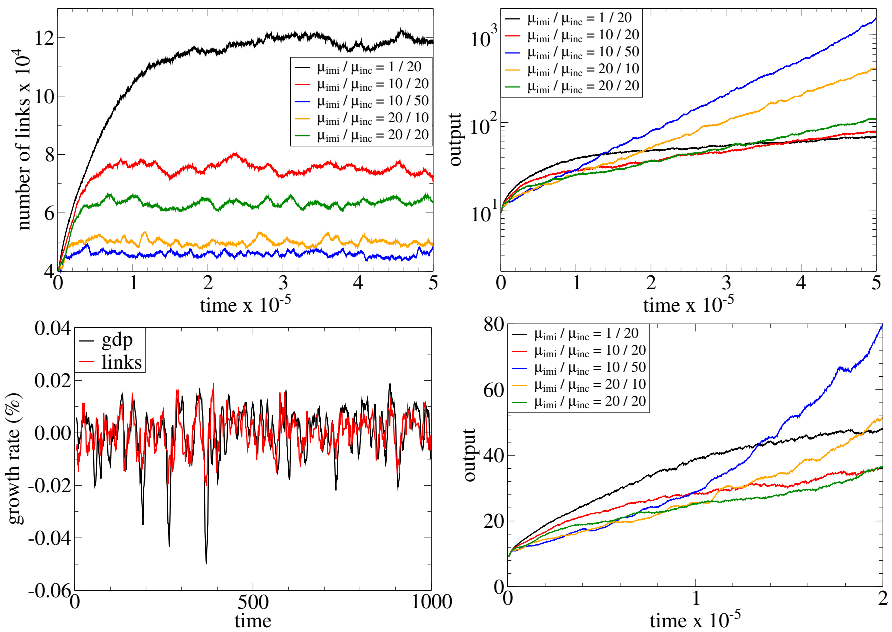

Figure 5: Evolution of the number of links (upper left) and of total output (upper and lower right) for representative simulations with varying imitation and incremental innovation rates. The lower left panel displays the joint evolution over 100000 periods of the growth rate of links and output for a representative simulation. Other parameters are set as in table 1.

These business cycles correspond to an amplified version of the interactions between the radical and incremental innovation processes analyzed above. The upswings of connectivity cycles correspond to the accumulation of incremental innovations as illustrated in the lower left panel of figure 5, which shows the very strong correlation between growth of output and connectivity. The downswings correspond to the occurence of radical innovations, amplified by imitation, that disrupt the industry. The amplitude and the period of these cycles increase with the μ_{im}/μ_{rad} ratio, that is as the frequency of radical innovations decreases and the role of imitation increases.

The fluctuations of output are strongly correlated with connectivity. Output grows with connectivity, i.e while technologies get more mature (see the lower left panel of figure 5). Accordingly the growth rate of output increases with the rate of incremental innovation (see the lower right panel of figure 5). Radical innovations destroy links and disrupt the production structure. Therefore, they have a negative impact on output in the short term. However, they pave the way for future growth as they allow for a new wave of incremental innovations to occur.

The contrast between figure 4 and 5 highlights the crucial role of imitation in the emergence of fluctuations. Indeed, imitation amplifies the synchronization of technological evolution among firms. It leads to the emergence, from the micro-economic behavior of distinct technological phases where product/radical and process/incremental innovation successively dominate. This pattern is reminiscent of empirical observations about the development of technologies described e.g in the Utterback-Abernathy model [see Utterback, 1994].

The structural evolution of the network is also aligned with key empirical facts about the demographics of firms. The distribution of firms' sizes, measured through their indegree distribution in figure 6, is characterized by fatter tails than normal, though the scale-free character is absent given that we consider here relatively large rate of innovation that imper the formation of very large firms. The outdegree distribution of firms in the right panel of figure 6 measures the variability of productivity (through variety in the input mix) in the population of firms. This distribution underlines the persistence of heterogeneity among firms in terms of productivity and the fact that this heterogeneity increases with the rate of incremental innovation that allows a deeper exploration of the technological paradigm.

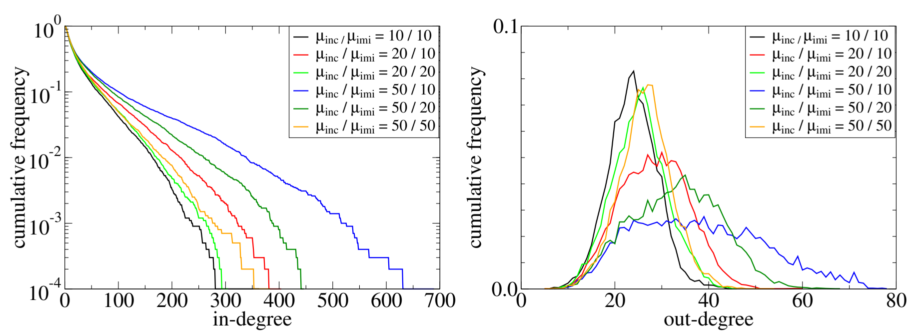

Figure 6: Distribution of in-degrees (left, log-linear) and out-degrees (right) after 2.10^6 periods for varying imitation and incremental innovation rates. Other parameters are set as in table 1.

4.4 Firms' demographics

More broadly, the model is able to replicate a wealth of stylized facts about industrial dynamics (see e.g Coad [2009]):

- As illustrated in the left panel Figure 7, growth rates of firms are distributed according to a "tent-shaped" double-exponential distribution (see

Bottazzi and Secchi [2006]). Moreover, the right tail of the distribution thickens with the increasing share of imitative and radical innovation.

- There is a negative relation between the variance of growth rate and the size of firms. In absence of radical innovation, there moreover is a scaling relation, of the form $\sigma(s) = s^{-\beta}$ where s is the size of the firm and $\sigma(s)$ is the variance of growth rates for firms of size s.

- As illustrated in the right panel of Figure 7, the distribution of product's productivity (the e_js) is heterogeneous ; it exhibits much fatter tails in absence of imitation. Together with the above results about the outdegree distribution of firms, it implies that the model endogenously generate heterogeneity both in terms of process and of product productivity.

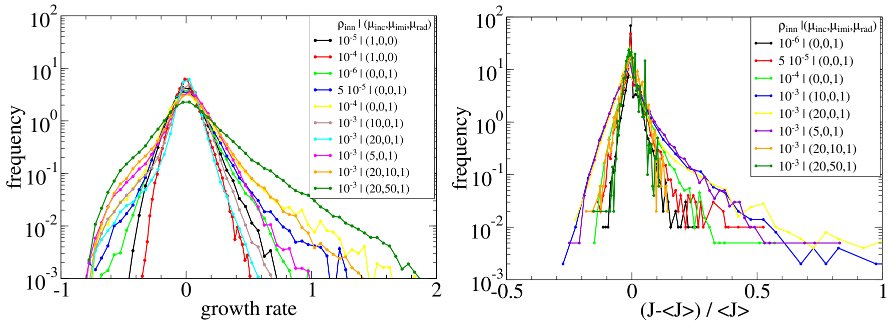

Figure 7: Distribution of growth rates (left) and of products' productivity (right) for varying rates of innovation.

5 Policy experiments

The preceding section puts forward the crucial role of radical innovation in sustaining growth in our model. This strongly echoes the emphasis on innovation and industrial policy in contemporary economies. A prominent example in the current policy debate is the energy industry where innovations in renewables energy production, which are crucial for climate change mitigation, are seen as potential drivers of "green" economic growth [see e.g Tàbara et al., 2013]. A key policy question then is whether growth can be stimulated through measures supporting radical innovations. In the context of energy markets, the main measures put in place were on the one hand feed-in tarifs, which consist in subsidizing the price paid to renewable energy producers and on the other hand preferential access to the market for renewable energy producers[2].

[2] A cautionary note in this respect is that, as argued by Lamperti et al. [2015], market-based policies may not be sufficient to prevent environmental disasters (while Command-and-Control policies are fully effective).

Accordingly, we investigate in the model the impact of price-based and market access-based measures on the survival rate of radical innovators and on the growth rate of the economy. In a first series of experiments, we focus on the aggregate impact of these measures and do not differentiate between sectors. More precisely, we consider the following scenarios.

- In the price-support scenario, which is akin to feed-in tariffs, the prices of radical innovators are subsidized during 200 periods after an innovation occurred. More precisely, if firm i performed a radical innovation less than 200 periods ago, the price paid by its consumers is $(1 - \tau_{feed})p_i^t$ rather than p_i^t. We assume that the difference between buying and selling prices is financed by the government through external deficit[3].

- In the market-support scenario, akin to preferential market access, firms are set to rewire prioritarily to radical innovators when they update their suppliers (see equation 2). The length of time after their innovation for which firms are given priority access, T_{pr} is the policy variable.

For each policy scenario, we perform a series of monte-carlo simulations where we let vary the policy parameter, respectively in $\{0.1, 0.2, 0.5\}$ for τ_{feed} and in $\{100, 500, 1000\}$ for T_{pr}. Other parameters are set as in section 4.3 with $^{\mu_{im}}/_{\mu_{rad}} \in \{0, 1\}$ and $^{\mu_{inc}}/_{\mu_{rad}} = 1$. Simulations are ran for five different seeds for each combination of parameters.

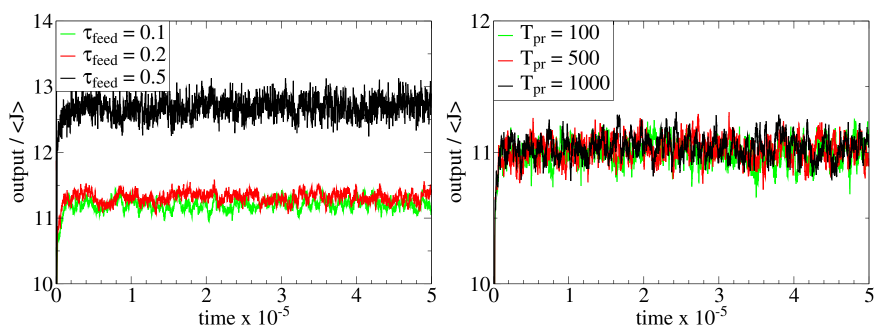

Figure 8: Evolution of outptut (normalized by average product productivity J) for the price-support (left) and the market-support (right) scenarios. In both cases, one has $\rho_{inn} = 10^{-3}$, $\mu_{incr} = \mu_{imi} = \mu_{rad}$ and other parameters are set as in table 1.

As illustrated in Figure 8 and Table 3 respectively, only the price-support policy has an impact on survival probabilities and hence on output. This suggests that price-support measures have, in our framework, a stronger impact on the competitive position of firms. Moreover, the market-support policy only

[3]In fact, everything goes as of the economy was receiving an external subsidy.

price-support scenario		market-support scenario	0
parameter	exit rate	parameter	exit rate
$\mu_{im} = 0, \tau_{feed} = 0.1$	3.10^{-2}	$\mu_{im} = 0, T_{pr} = 100$	3.10^{-2}
$\mu_{im} = 0, \tau_{feed} = 0.2$	8.10^{-3}	$\mu_{im} = 0, T_{pr} = 500$	4.10^{-2}
$\mu_{im} = 0, \tau_{feed} = 0.5$	5.10^{-4}	$\mu_{im} = 0, T_{pr} = 1000$	5.10^{-2}
$\mu_{im} = 1, \tau_{feed} = 0.1$	2.10^{-2}	$\mu_{im} = 1, T_{pr} = 100$	2.10^{-2}
$\mu_{im} = 1, \tau_{feed} = 0.2$	6.10^{-3}	$\mu_{im} = 1, T_{pr} = 500$	3.10^{-2}
$\mu_{im} = 1, \tau_{feed} = 0.5$	3.10^{-4}	$\mu_{im} = 1, T_{pr} = 1000$	4.10^{-2}

Table 3: Exit rate of radical innovators(per 10^3 periods)

shifts demand within the economy while the price-support policy provides, at the aggregate level, a subsidy to the economy by financing externally the price reduction for radical innovators. This subsidy can yield a demand-push and indirectly trigger multiplier effects.

The impact on output in the price-support scenario materializes, both with and without imitation, by the increase of the output per productivity unit ratio, where the latter is measured by the average *product productivity* (see Figure 8). This implies that firms have, in average, a more efficient/diversified production process, i.e that they have seized more incremental innovations. This feature is clearly consistent with the decreased rate of exit for radical innovators: if firms leave longer, they have more opportunities to seize incremental innovations.

The impact on aggregate output is more ambiguous. Figure 9 suggests that the price-support policy has a negative impact in absence of imitation and a neutral (or slightly positive) impact in presence of imitation. This presumably is the counterpart of the increased lifespan of radical innovators. If incumbent innovators are more efficient, it is harder for a new radical innovation to succeed and hence the growth rate of productivity is reduced. This effect is partly offset by imitation, which allows to diffuse increased productivity directly among incumbents.

In the context of climate change, policy also aims at directing technological change towards specific sectors (e.g. green vs fossil energy use). We investigate this more focused type of policies in a second series of experiments where we consider that the price-support policy is implemented in a single sector. TODO complete More precisely, we consider that...The results of these experiments are illustrated in Figure xx. They show that that policy can direct technological change with/without affecting the growth rate of output. Details about these new results are provided at the end of section 5 ??

It is clearly inappropriate to draw direct policy conclusions from simple experiments performed in such a stylized framework. However, we would argue that our results underline that the impact of policy strongly depends on the kind of externalities in the economy under consideration. The main external effect on innovation in our framework is imitation for which only the most efficient producers matter. If we were to consider stronger complementarities between innovators, the survival of a larger share of innovators might have a much more significant impact on growth.

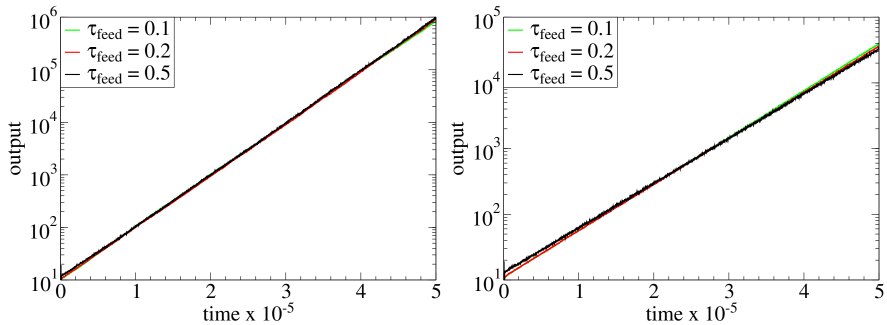

Figure 9: Evolution of outptut (log scale) for the price-support scenario with (left) and without (right) imitation.

6 Concluding remarks

We have developed a macro-economic agent-based model centered on the evolution of production networks. The structure of the network, i.e the structure of the market, constrains firm's behavior in the short-run and hence determines short-term economic dynamics. In turn, competition among firms and technological innovations govern the evolution of the network. Long-term macroeconomic dynamics hence emerge from the micro-economic interactions among firms.

From the theoretical point of view, our main innovation is to provide a detailed micro-economic representation of the production process, accounting for intermediary consumption, within a growing economy. Technological progress is embedded in the structure of the network and we consider two avenues for growth. Process innovation, which materializes through diversification of the input mix and hence increasing connectivity in the network. Product innovation, which induce a direct increase of productivity at the expense of a temporary loss of specialization in the production process and hence decreasing connectivity. These two processes can respectively be interpreted as the decentralization of the two workhorses of endogenous growth theory, product variety model à la Romer [1990] and "Schumpeterian" growth model à la Aghion and Howitt [1992], in a micro-economic setting with boundedly rational agents.

Considering innovation occurs at the micro-level and accounting for the local nature of interactions allow to reproduce a wealth of stylized facts that the aggregate nature of endogenous growth models discards by construction. Growth is exponential in the aggregate and follows Wright's law within a technological paradigm. The distribution of productivity among firms is heterogeneous. The distribution of firms' size exhibit fat-tails whose thickness depends on the aggregate rate of growth.

Additionally, imitation can lead to the synchronization of firms' innovative behavior and hence to the emergence of growth patterns in which process/incremental and product/radical innovation successively dominate, as in the Utterback-Abernathy model [see Utterback, 1994]. This cyclicality of the innovation process induces technologically driven business cycles. Process innovation and increasing connectivity coincide with upswings, product innovation and decreasing connectivity with downswings.

The large number of stylized facts the model is able to reproduce and the richness of the dynamical patterns observed in simulations suggest that the model could be a useful testbed for the analysis of industrial and innovation policies, in particular in the context of the energy transition. In this view, we perform a first series of policy experiments in which we investigate the impact of feed-in tariffs and of priority access to the market on the survival rate of innovators and growth. Our results underline the fact that the impact of policy crucially depends on the nature of externalities among innovators. If imitation dominates, only the most efficient firms matter and these can survive without public support.

Yet, an important avenue for future research is to account for other form of external effects in the innovation process, for the role of institutions and for the broader socio-economic landscape in which innovation is developed [see e.g Saxenian, 1996, in these respects]. Another important aspect that requires further investigation is the role of the demand in the development of innovations. In this respect, it might be worth investigating the emergence of demand among heterogeneous households that might not necessarily be characterized by preferences for goods but rather by Lancasterian preferences for characteristics [Lancaster, 1966].

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A General Equilibrium and Production Networks

A.1 A general equilibrium economy

One can associate to a production network A a general equilibrium economy as follows:

Definition 1 *The general equilibrium economy $\mathcal{E}(A)$ is defined by the given of:*

- *A representative household supplying one unit of labor and having preferences represented by the Cobb-Douglas utility functiion $u(x_1, \cdots, x_m) = \prod_{i=1}^{m} x_i^{\alpha_{0,i}}$*
- *A set of firms M with production functions of the form*

$$f_i(x_0, (x_j)_{j=1,\cdots,n_i}) = x_0^{\alpha}(\sum_{j=1}^{n_i} x_j^{\theta})^{(1-\alpha)/\theta} \tag{6}$$

- *A production network A consistent with equation* (6) *in the sense that for all $i \in M$, $\sum_{j=1}^{m} a_{i,j} = n_i$.*

A.2 Out-of-equilibrium Dynamics

For a given network, the dynamics of prices and output follow from the application of simple behavioral rules. More precisely, given a production network A the dynamics of wealth $w_i^t \in \mathbb{R}_+$, output $q_i^t \in \mathbb{R}_+$ and prices $p_i^t \in \mathbb{R}_+$ within period t are determined as follows.

1. Each agent i receives the nominal demand $\sum_{j \in N} \alpha_{i,j}^t w_j^t$, which is implied by the current structure of the supply network

2. Agents adjust their prices frictionally towards their market-clearing values according to:
$$p_i^t = \tau_p \overline{p}_i^t + (1 - \tau_p) p_i^{t-1} \tag{7}$$
where $\tau_p \in [0, 1]$ is a parameter measuring the speed of price adjustment and, given the nominal demand $\sum_{j \in N} \alpha_{i,j}^t w_j^t$ and the output stock q_i^t, $\overline{p}_i^t$ is the market clearing price for firm i, that is:
$$\overline{p}_i^t = \frac{\sum_{j \in N} \alpha_{i,j}^t w_j^t}{q_i^t}. \tag{8}$$

3. Whenever $\tau_p < 1$ markets do not clear (except if the system is at a stationary equilibrium). In case of excess demand, we assume that clients are rationed proportionally to their demand. In case of excess supply, we assume that the amount $\overline{q}_i^t := \sum_{j \in N} \alpha_{i,j}^t w_j^t / p_i^t$ is actually sold and that the rest of the output is stored as inventory. Together with production occurring on the basis of purchased inputs, this yields the following evolution of the product stock:
$$q_i^{t+1} = q_i^t - \overline{q}_i^t + f_i\left(\frac{\alpha_{0,i}^t w_i^t}{p_0^t}, \left(\frac{\alpha_{j,i}^t w_i^t}{p_j^t}\right)_{j \in \Sigma_i(A^t)}\right) \tag{9}$$
Note that in the case where $\tau_p = 1$, markets always clear (one has $\overline{q}_i^t = q_i^t$) and equation (9) reduces to
$$q_i^{t+1} = f_i\left(\frac{\alpha_{0,i}^t w_i^t}{p_0^t}, \left(\frac{\alpha_{j,i}^t w_i^t}{p_j^t}\right)_{j \in \Sigma_i(A^t)}\right) \tag{10}$$

4. As for the evolution of agents' wealth, it is determined on the one hand by their purchases of inputs and their sales of output. On the other hand, we assume that the firm sets its expenses for next period at $(1 - \lambda)$ times its current revenues and distributes the rest as dividends to the representative household. That is one has:
$$\forall i \in M, \; w_i^{t+1} = (1 - \lambda) \overline{q}_i^t p_i^t \tag{11}$$
$$w_0^{t+1} = q_0^t p_0^t + \lambda \sum_{i \in M} \overline{q}_i^t p_i^t \tag{12}$$

Note that equation (12) can be interpreted as assuming that firms have myopic expectations about their nominal demand (i.e they assume they will face the same nominal demand next period) and target a fixed profit/dividend share $\lambda \in (0,1)$.

5. As for the evolution of input shares, agents adjust frictionally their input combinations towards the cost-minimizing value according to:

$$\alpha_i^{t+1} = \tau_w \overline{\alpha}_i^t + (1-\tau_w)\alpha_i^t \tag{13}$$

where $\tau_w \in [0,1]$ measures the speed of technological adjustment and $\overline{\alpha}_i^t \in \mathbb{R}^M$ denotes the optimal input weights for firm i given prevailing prices. Those weights are defined as the solution to the following optimization problem:

$$\begin{cases} \max & f_i(\frac{\alpha_0, i}{p_0^t}, (\frac{\alpha_j, i}{p_j^t})_{j\in\Sigma_i(A^t)}) \\ \text{s.t} & \sum_{j\in\Sigma_i(A^t)} \alpha_{j,i} = 1 \end{cases} \tag{14}$$

A.3 Convergence

These behavioral rules in fact define out-of-equilibrium dynamics in the economy $\mathcal{E}(A)$. Their asymptotic properties are extensively studied in [Gualdi and Mandel, 2015]. In particular, for a fixed network and over a vast region of the parameter space, one observes convergence to a general equilibrium of the underlying economy with a fixed mark-up rate λ. It corresponds to general equilibrium in the common-sense if $\lambda = 0$ and is defined as follows:

Definition 2 *A λ-mark-up equilibrium of the economy $\mathcal{E}(A)$ is a collection of prices $(p_0^*, \cdots, p_n^*) \in \mathbb{R}_+^M$, production levels $(q_0^*, \cdots, q_n^*) \in \mathbb{R}_+^M$ and commodity flows $(x_{i,j}^*)_{i,j=0\cdots n} \in \mathbb{R}_+^{M\times M}$ such that:*

- *Markets clear. That is for all $i \in M$, one has*

$$q_i^* = \sum_{j=1}^{M} x_{i,j}^*.$$

- *The representative consumer maximizes his utility. That is $(q_0^*, (x_{0,j}^*)_{j=1,\cdots,n})$ is a solution to*

$$\begin{cases} max\ u_i((x_{0,j})_{j=1,\cdots,n}) \\ \\ s.t\ \sum_{j=1}^n p_j^* x_{0,j}^* \leq 1 \end{cases}$$

(with the price of labor normalized to 1)

- *Production costs are minimized. That is for all $i \in M$, $(x_{i,j}^*)_{j=0\cdots n}$ is the solution to*

$$\begin{cases} min & \sum_{j\in\Sigma_i(A)} p_j^* x_j \\ s.t & f_i(x_j) \geq q_i^* \end{cases}$$

- *Prices are set as a mark-up over production costs at rate* $\dfrac{\lambda}{1-\lambda}$. *That is one has for all* $i \in N$:

$$p_i^* = (1 + \frac{\lambda}{1-\lambda})\frac{\sum_{j\in\Sigma_i(A)} p_j^* x_{i,j}^*}{q_i^*}$$