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

T. Balint[a], F. Lamperti[b], A. Mandel[a], M. Napoletano[b,c], A. Roventini[b,c], A. Sapio[d]

[a] *Université Paris 1 Panthéon-Sorbonne and CNRS*
[b] *Institute of Economics and LEM, Scuola Superiore Sant'Anna (Pisa)*
[c] *OFCE-Sciences Po (Nice)*
[d] *Parthenope University of Naples*

Abstract

Climate change is one of the most daunting challenges human kind has ever faced. In the paper, 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.

*Corresponding author
Email address: `f.lamperti@santannapisa.it` (F. Lamperti)

1. Introduction

Climate change is one of the most daunting challenges human kind has ever faced. In the paper, we provide a survey of the economics of climate change from a complexity science perspective and underline the benefits and 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 embedded 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 may convey a false impression of control (see Ackerman et al., 2009; Pindyck, 2013; Stern, 2013; Weitzman, 2013; Revesz et al., 2014; Farmer et al., 2015, among many contributions) and that IAMs may underestimate both the cost of climate change and the benefits resulting from the transition to a low carbon-emission economy (Stern, 2016).Moreover, IAMs do not account for feedback loops from climate change to the economy and finance, and for climate policy reflexivity as a result of both climate change impact and agents responses at the micro-level. This is due to both the structural characteristics of IAMs such as the lack of financial sector and key variables such as labour productivity, technology, resource use and population that are left exogenous, and to behavioural characteristics such as equilibrium paradigm, representative, utility maximizing agent, the rather arbitrary assumptions used to set the discount rates as well as the absence of distributional issues (inequality formation).[1] These are the main reasons to prefer complex systems approaches to IAM for the study of the economics of climate change.

Network and agent-based models (ABMs) 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; Battiston et al., 2016). These classes of models consider the real world as a *complex evolving system*, wherein the interactions 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 consider the possible catastrophic effects of climate change and the urgency and opportunities of policy responses. Moreover, ABMs can ease stakeholder participation and scenario exploration (Moss et al., 2001; Moss, 2002a). Indeed, their higher degree of realism (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

[1] 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 for the IPCC reviews, despite being mostly CGE based, are employed to project socio-economic conditions under different scenarios and to assess different mitigation pathways. See Clarke et al. (2009) for an overview of main models and Stanton et al. (2009) for a critical discussion on their results.

economics of climate change, focusing in particular on agent-based, network and system dynamics 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.[2] 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.

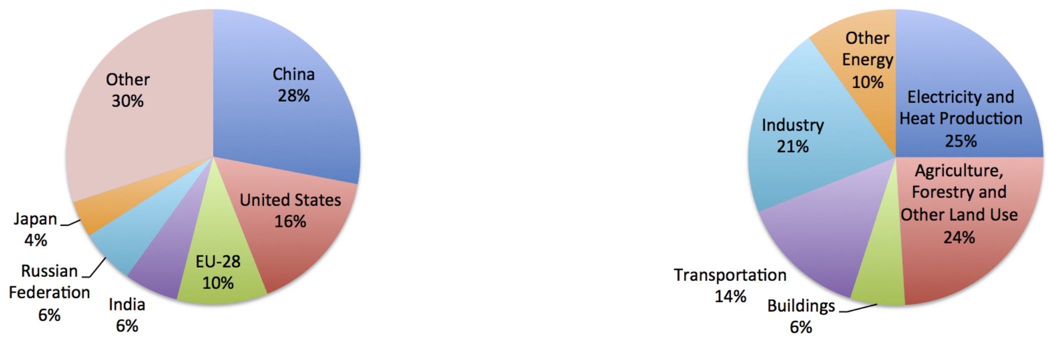
Third, we consider the functioning of the energy sector, which is by far the largest emitter of green-house gases globally (see Section 4). In this field, deregulation (especially in electricity market) has pushed modelers to shift their attention from monopoly and oligopoly settings to complex structures 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 comparison of equilibrium and complex system models in studying the micro and macro economics of climate change (see Section 6) in light of the four domains surveyed in the paper. Our general conclusion is that current equilibrium models are not fit to cope with the phenomena associated with an increasingly warming planet, such as non-linear effects, tipping points, irreversibilities, catastrophic

[2] 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).

events. Given the ensuing formidable societal challenges posed by climate change, researchers should increasingly embrace agent-based and network models, which appear to be the most promising theoretical option. In Section 7, we suggest the potential research directions to further improve such models in order 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 are 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 argue 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.

Furthermore, 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

Adding to the insights about the workings of the international negotiation process which we have reviewed, Downing et al. (2001) put forward as a prototype ABM of water management for stakeholder engagement in the design of climate policies, with an application to the Thames region of England (see also Tesfatsion et al., 2017 for recent and promising developments). 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.[3] Second, climate and macroeconomic dynamics occur at different time scales. Third, the poor understanding of human responses to a warmer weather and to extreme weather events complicates the characterization of climate damages.

From an aggregate perspective, System Dynamics (SD, Forrester, 1958) models provide a flexible tool to explore the complex interactions between climate and economic dynamics, helping to shed light on extreme events, catastrophes and regimes switches, which are at the core of climate change issues. SD models have the advantage of naturally embedding non-linear dynamics, multiple time scales and feedback loops in the toolbox. As a complementary approach to modeling complex, out-of-equilibrium economies, macro ABMs 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).

We shall review how network and agent-based models manage to represent climate-related damages considering distributional issues and the role of system connectivity. In addition, we shall explore their applications 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).[4]

[3] 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.

[4] Beyond SD and ABMs, a complementary perspective is offered in this journal's special section on Ecological Macroeconomics Rezai and Stagl (2016).

3.1. System Dynamics models

SD models rely on computer simulations to project the behavior of non-linear systems characterized by the presence of feedback loops.[5] They study out-of-equilibrium dynamics of complex systems employing aggregate equations, without explicitly modeling agents' heterogeneity and interactions.

The first application of a SD-like model (called World3) to the issue of sustainable development can be traced back to the Limits to Growth report (Meadows et al., 1972).[6] Despite the relative simplicity of the underlying model (the focus was on five main variables), the report has been able to highlight the risks stemming from uncontrolled growth patterns, which could end up in global collapse scenario. However, the model does not include a climate side. This was introduced in Fiddaman (1997), which is amongst the first attempts to use a SD model for integrated assessment of complex climate-economy structures. In recent years, a variety of models have been developed to test policy intervention in a world characterized by non-linear dynamics within the climate system (Mastrandrea and Schneider, 2001; Fiddaman, 2002; Sterman et al., 2012, 2013), the economic system (Monasterolo and Raberto, 2016) or both (Akhtar et al., 2013; Siegel et al., 2015). Despite these modeling efforts account for feedbacks loops, non-smooth aggregate behavior and multiple equilibria, they are often coupled with microeconomic assumptions that are very closed to those embraced by standard CGE frameworks. For instance, the MADIAMS family of model (Hasselmann, 2010; Hasselmann and Kovalevsky, 2013; Kovalevsky and Hasselmann, 2014) comprise a multi-actor SD-based integrated-assessment model for climate policy analysis, which allows for different industries, actors, regions and for their interactions, but assume agent homogeneity and utility maximization.

We think that the cross-fertilization between SDs and ABMs is very promising as it could give the opportunity to gradually introduce heterogeneity, network structures and boundedly-rational behavior and to separately identify the impact of such additions on macro level phenomena (e.g. likelihood of green transition or emissions' growth rate).[7] This is even more urgent if one considers that as SD models are naturally rooted in catastrophe theory (Thom, 1976, 1977; Zeeman, 1977), they allow to study the "catastrophic" features of the coupled climate-societal system, which might be subsequently used to inform the development of ABMs adding heterogeneity and interactions to the initial aggregate picture.

3.2. 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.[8] Notwithstanding

[5]System dynamics simulation approach originates from the pioneering work of Forrester (1958) in the field of business management. Today, SD simulation is employed in various disciplines of natural, social and health sciences.

[6]The analysis has been subsequently updated in Meadows et al. (1992) and Meadows et al. (2004). See also Pasqualino et al. (2015) and Bardi (2011) for more recent developments.

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

[8]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).

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, 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 occur 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.[9] 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, 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

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

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 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.

3.3. 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, works in the complex system approach have modeled the emergence of aggregate damages as resulting from micro shocks in production, procurement or finance propagating across 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.[10] The model has also been employed 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.[11]

[10]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).

[11]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.

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 weeks), price adjustment mechanisms are nearly absent at the current stage and technical change is overlooked.

3.4. Integrated assessment agent-based models

Despite the methodological advantages that agent-based models 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.[12] To the best of our knowledge, Lamperti et al. (2016) introduces the first attempt to bridge a 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).

3.5. 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

[12] 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.

(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 (Lazarus and Tempest, 2014; Carney, 2015; Fulton and Weber, 2015). 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 and pension 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.

3.6. Open issues

Our understanding of the aggregate effects produced by climate change on the economic system is still limited. 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 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).[13]

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 of a large number of micro-generators, characterized by unpredictable generation profiles, in the existing transmission and distribution networks 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 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

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

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).[14]

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.

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

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

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,[15] 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 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,[16] 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.[17] Recent evidence on the diffusion of environmentally-friendly technologies can be found in Narbel (2013).

In standard neoclassical economics, knowledge is nearly synonymous to codified 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

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

[16] 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).

[17] 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 is hardly predictable. Hence, it finds a formidable barrier to its diffusion.

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.[18]

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

Time and agent heterogeneity have long been recognized as two central features of all technology diffusion processes (Silverberg et al., 1988, see e.g.). Agents have indeed different incentives and/or face different constraints in the adoption of innovations. Adoption decisions by agents following heuristics may be characterized by various degrees of inertia, implying longer adoption lags than with a homogenous optimizing population. Also, since early adopters are typically in the top quantiles of the income distribution, income inequality may stimulate the introduction of a new technology but it may slow down further diffusion. It follows that, in the context of green technology diffusion, the extent of agents' heterogeneity may accelerate regime transitions or, alternatively, contribute to lock the system in the existing state. The need to account for agents' heterogeneity in its various instances, such as income inequality is increasingly recognized in climate change economics and policy (see e.g. Dennig et al., 2015). ABMs exploring how green technology adoption paths are affected by the heterogeneity in individual behaviors and preferences have been proposed by Windrum et al. (2009), which we summarize in what follows, as well as by Janssen and Jager (2002) and Schwoon (2006).

In particular, Windrum et al. (2009) study how heterogeneous consumer 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 revise 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.

Behavioral heterogeneity may also stem from inequality in endowments across agents. Recent experimental studies (e.g. Tavoni et al., 2011) focusing on public goods games provide evidence that excessive inequality across agents may undermine the provision of the total effort necessary to avoid catastrophic climate change outcomes. Likewise, excessive income inequality may create a serious gap in adoption times between the rich and the poor that is difficult to bridge, unless appropriate policies are designed. The latter 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,

[18]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).

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) is 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 take account of agent heterogeneity and direct non-price interactions, but are still unable to fully 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).[19] Secondly, ABMs still do not capture some 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. Discussion

A strong contrast between equilibrium- and complexity-based models emerges from our survey of the literature on the economics of climate change. Such differences are summarized in Table 1, which provides a comparison between the structural characteristics and the domain of application of the equilibrium-based, agent-based and System Dynamics models.

The equilibrium-based literature takes the structural elements of the economy as given and in such a setting computes the optimal response to climate policy and impacts. The instantaneous adjustment of prices guarantees that the economy is always on the optimal pathway. As the current economic structure has been built around fossil-based supply of energy and without concern for greenhouse gases emissions, equilibrium models lead to impossibility results when it comes to the implementation of climate policy: impossibility to reach an international climate agreement, to shift massively to renewable energy sources or, more broadly, to move to greener paths of economic growth. On the contrary, considering the decentralized interactions of heterogenous individuals, ABMs take climate policy objectives as given and then study how climate policies could be implemented at the micro-level and which evolution of the economic structure they could trigger. This approach allows to identify potential pathways and barriers towards the implementation of climate policy objectives in a variety of context: international negotiations, energy policy, industrial policy, monetary and fiscal policy. SD models offer a similar perspective, but from the macro-level. In that, they do not allow to analyze in details the implementation of policies or their distributional impacts.

As for climate impacts, equilibrium-based integrated assessment models have been fiercely criticized for averaging out climate impacts and hence discarding the low-probability and high-risk impacts that constitute the main socio-economic threat from climate change (Pindyck, 2013). On the contrary, agent-based models are fit to address this critique as they allow to consider arbitrary distributions of shocks hitting agents at the micro-level and to simulate their possible catastrophic impact via economic and financial networks. Similarly, SD models

[19] 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 diffusion of more eco-friendly production processes.

allows for disasters and non-linear feedback loops, but only in an aggregate framework.

The economic assessment of climate shocks and policies is carried out in equilibrium-based model computing the social well-being of a representative agent with debatable assumption concerning e.g. the discount rate (Pindyck, 2013). Such an assessment occur at the macroeconomic level as in system dynamics models. Agent-based models allow instead to assess both the macro- and micro-economic impact of climate events, taking also into account the possible distributional consequences. Moreover, they endogenously account for technological and structural change processes.

Equilibrium-based model are calibrated according to social accounting matrices and exogenous scenarios. The complex system perspective of ABM imply that they are difficult to calibrate or estimate (Fagiolo and Roventini, 2017). However, efforts directed at improving these models' empirical validation toolbox are rapidly increasing (Gilli and Winker, 2003; Franke and Westerhoff, 2012; Barde, 2016; Grazzini et al., 2015; Guerini and Moneta, 2016; Lamperti, 2016, 2017), and the results appear promising. Given their relatively simpler macroeconomic structure, SD models are instead easier to calibrate.

Such differences between equilibrium and agent-based model is mirrored in the way they relate to the climate policy domains considered in Sections 2-5 above (cf. Table 2).[20] The comparison suggests that agent-based models provide a richer toolbox to support the implementation and assessment of different ensembles of climate policies. For instance, in contrast with equilibrium models, which consider the economic structure as given, ABMs reserve an important role for finance, they consider barriers in achieving international environmental agreement, they account for institutional and technical complexity of electricity markets, and they study how technological innovation and diffusion interact with climate change. In that respect, system dynamics models can be a useful companion.

Table 1: Methodological comparison of different modeling approaches

	Equilibrium-based models	**System Dynamics**	**Agent-Based Models**
Modeling paradigms	Coordination via instantaneous price adjustment and rational expectations generates a unique equilibrium path defining the only possible pathway for the economy	Set of non-linear dynamic equations describing the climate-economy system at the macro-level. Sensitivity to policy and coupling define a set of potential economic trajectories	Decentralized coordination via interactions of heterogenous agents. A set of potential climate-economic trajectories emerge from micro-level behaviors in Monte-Carlo experiments
Representation of climate impacts and feedback loops	Impacts are averaged out at sectorial or macro-level, through a (sublinear) damage function. Feedback effects only via prices	Macro-level impacts governed by non-linear feedback loops with delays	Distribution of impacts at the micro-level and propagation through socio-economic networks with delays in the adjustment of process
Economic assessment	Macro-economic impacts and "social well-being" of a representative agent	Macro-economic impacts	Macro-economic and distributional impacts. Structural and technological change
Calibration and estimation	Calibration based on social accounting matrices and exogenous scenarios about future economic dynamics	Calibration based on macro-level data	Calibration requires large micro-economic dataset. Estimation might be highly demanding in terms of computational power

[20] We do not include system dynamics model in Table 2 as their aggregate structure allows them to be employed only in macroeconomic assessment of climate change and policies.

Table 2: Applications of different modelling approaches

	Equilibrium-based models	**Agent-Based Models**
Credit and finance	Irrelevant as markets are complete and information is perfect	Information asymmetries and regulatory constraints affect investment and production decisions. Emergence of network-based financial accelerator
International environmental agreements	Only global agreements given the public good nature of climate protection	Identify barriers and leverage points in the dynamics of the political process that could foster (or hamper) broader cooperation
Macro policy assessment	Climate policy as an additional cost on the single equilibrium growth path	Climate policy as an opportunity. Multiple equilibria with the possibility of green growth paths
Energy markets	Characterization of optimal, equilibrium behavior in a stylized settings	Models accounting for the institutional and technical complexity of the electricity market
Technological innovation and diffusion	Irrelevant or represented as an externality	Analyzed through learning, imitation and information diffusion models

7. 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 analyze 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 is fundamental to single out the possible catastrophic events of climate change and design an ensemble of policies to put the economy on a sustainable steady growth path. Not surprisingly, agent-based models are increasingly considered as a prominent alternative to standard general-equilibrium models, which overlook many of the risks of climate change (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 compare complex system models with equilibrium ones, and discussed the open challenges. The surveyed fields encompass climate negotiations and the formation of coalitions, macroeconomic and financial aspects linked to climate change, which include (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 met. One of them concerns the relationship between inequality and climate damages. Another deals with the effects of agents' interconnectivity on climate policies and on the systemic stability of production and financial networks. These are major issues that complexity theory models of climate change are starting to investigate, and that would be extremely difficult to analyze in 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 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 ABMs should provide a better account of the interrelations between financial markets, the real economy and climate change. How can financial markets promote or

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.

Acemoglu, D., P. Aghion, L. Bursztyn, and D. Hemous (2012). The environment and directed technical change. *American Economic Review 102*(1), 131–66.

Ackerman, F., S. J. DeCanio, R. B. Howarth, and K. Sheeran (2009). Limitations of integrated assessment models of climate change. *Climatic change 95*(3), 297–315.

Akhtar, M. K., J. Wibe, S. P. Simonovic, and J. MacGee (2013). Integrated assessment model of society-biosphere-climate-economy-energy system. *Environmental modelling & software 49*, 1–21.

Allan, C., A. B. Jaffe, and I. Sin (2014). Diffusion of green technology: a survey. *International Review of Environmental and Resource Economics 7*(1), 1–33.

Anaya, K. L. and M. G. Pollitt (2015). Integrating distributed generation: Regulation and trends in three leading countries. *Energy Policy 85*, 475–486.

Balbi, S. and C. Giupponi (2010). Agent-based modelling of socio-ecosystems: A methodology for the analysis of adaptation to climate change. *International Journal of Agent Technologies and Systems 2*(4), 17–38.

Banal-Estanol, A. and A. Ruperez Micola (2011). Behavioural simulations in spot electricity markets. *European Journal of Operational Research 214*(1), 147–159.

Barde, S. (2016). A practical, accurate, information criterion for Nth order markov processes. *Computational Economics*, 1–44.

Bardi, U. (2011). *The limits to growth revisited.* Springer Science & Business Media.

Bardoscia, M., S. Battiston, F. Caccioli, and G. Caldarelli (2015). Debtrank: A microscopic foundation for shock propagation. *PloS one 10*(6), e0130406.

Barrett, S. (1994). Self-enforcing international environmental agreements. *Oxford Economic Papers 46*, 878–894.

Bass, F. M. (1969). A simultaneous equation regression study of advertising and sales of cigarettes. *Journal of Marketing Research 6*(3), 291–300.

Battiston, S., J. D. Farmer, A. Flache, D. Garlaschelli, A. G. Haldane, H. Heesterbeek, C. Hommes, C. Jaeger, R. May, and M. Scheffer (2016). Complexity theory and financial regulation. *Science 351*(6275), 818–819.

Battiston, S., D. D. Gatti, M. Gallegati, B. Greenwald, and J. E. Stiglitz (2012). Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. *Journal of Economic Dynamics and Control 36*(8), 1121 – 1141. Quantifying and Understanding Dysfunctions in Financial Markets.

Battiston, S., A. Mandel, I. Monasterolo, F. Schuetze, and G. Visentin (2016). A climate stress-test of the eu financial system. mimeo, available at SSRN.

Battiston, S., M. Puliga, R. Kaushik, P. Tasca, and G. Caldarelli (2012, 08). Debtrank: Too central to fail? financial networks, the fed and systemic risk. *Scientific Reports 2*, 541 EP –.

Beale, N., D. G. Rand, H. Battey, K. Croxson, R. M. May, and M. A. Nowak (2011). Individual versus systemic risk and the regulator's dilemma. *Proceedings of the National Academy of Sciences 108*(31), 12647–12652.

Beckenbach, F. and R. Briegel (2010). Multi-agent modeling of economic innovation dynamics and its implications for analyzing emission impacts. *International Economics and Economic Policy 7*(2), 317–341.

Benchekroun, H. and D. Claude (2007). Tax differentials and the segmentation of networks of cooperation in oligopoly. *The BE Journal of Theoretical Economics 7*(1), 1–11.

Bierkandt, R., L. Wenz, S. N. Willner, and A. Levermann (2014). Acclimate—a model for economic damage propagation. part 1: basic formulation of damage transfer within a global supply network and damage conserving dynamics. *Environment Systems and Decisions 34*(4), 507–524.

Bleda, M. and M. Valente (2009). Graded eco-labels: a demand-oriented approach to reduce pollution. *Technological Forecasting and Social Change 76*(4), 512–524.

Boden, T., G. Marland, and R. Andres (2015). National CO2 emissions from fossil-fuel burning, cement manufacture, and gas flaring: 1751-2011. Technical report, Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy.

Boffa, F. and A. Sapio (2015). Introduction to the special issue "The regional integration of energy markets". *Energy Policy 85*, 421–425.

Borenstein, S., J. Bushnell, and S. Stoft (2000, Summer). The Competitive Effects of Transmission Capacity in A Deregulated Electricity Industry. *RAND Journal of Economics 31*(2), 294–325.

Bosetti, V., C. Carraro, M. Galeotti, E. Massetti, and M. Tavoni (2006). WITCH a world induced technical change hybrid model. *The Energy Journal 27*, 13–37.

Bosetti, V. and M. Maffezzoli (2013, September). Taxing Carbon under Market Incompleteness. Working Papers 2013.72, Fondazione Eni Enrico Mattei.

Bower, J. and D. Bunn (2001). Experimental analysis of the efficiency of uniform-price versus discriminatory auctions in the england and wales electricity market. *Journal of Economic Dynamics and Control 25*(3-4), 561 – 592. Agent-based Computational Economics (ACE).

Breton, M., L. Sbragia, and G. Zaccour (2010). A dynamic model for international environmental agreements. *Environmental and Resource Economics 45*(1), 25–48.

Brouwers, L., K. Hansson, H. Verhagen, and M. Boman (2001). Agent models of catastrophic events. In *Modelling Autonomous Agents in a Multi-Agent World, 10th European workshop on Multi Agent Systems.*

Browne, O., S. Poletti, and D. Young (2015). How does market power affect the impact of large scale wind investment in 'energy only' wholesale electricity markets? *Energy Policy 87*, 17–27.

Bruckner, T., R. Morrison, and T. Wittmann (2005). Public policy modeling of distributed energy technologies: strategies, attributes, and challenges. *Ecological Economics 54*(2–3), 328 – 345. Technological Change and the EnvironmentTechnological Change.

Buldyrev, S. V., R. Parshani, G. Paul, H. E. Stanley, and S. Havlin (2010, 04). Catastrophic cascade of failures in interdependent networks. *Nature 464*(7291), 1025–1028.

Bunn, D. W. and M. Martoccia (2005). Unilateral and collusive market power in the electricity pool of england and wales. *Energy Economics 27*(2), 305–315.

Bunn, D. W. and J. I. Munoz (2016). Supporting the externality of intermittency in policies for renewable energy. *Energy Policy 88*, 594–602.

Bunn, D. W. and F. S. Oliveira (2003). Evaluating individual market power in electricity markets via agent-based simulation. *Annals of Operations Research 121*(1), 57–77.

Cambini, C. and A. Rubino (2014). Regional energy initiatives in the mediterranean basin. In C. Cambini and A. Rubino (Eds.), *Regional Energy Initiatives: MedReg and the Energy Community*, pp. 1–10. London: Routledge.

Campiglio, E. (2016). Beyond carbon pricing: The role of banking and monetary policy in financing the transition to a low-carbon economy. *Ecological Economics 121*, 220 – 230.

Cantono, S. and G. Silverberg (2009). A percolation model of eco-innovation diffusion: The relationship between diffusion, learning economies and subsidies. *Technological Forecasting & Social Change 76*(4), 487–496.

Carney, M. (2015). Breaking the tragedy of the horizon-climate change and financial stability.

Castesana, P., S. Puliafito, et al. (2013). Development of an agent-based model and its application to the estimation of global carbon emissions. *Low Carbon Economy 4*(4), 24–34.

Clarke, L., J. Edmonds, V. Krey, R. Richels, S. Rose, and M. Tavoni (2009). International climate policy architectures: Overview of the emf 22 international scenarios. *Energy Economics suppl. 2*(31), S64–S81.

Cochrane, H. (2004). Economic loss: myth and measurement. *Disaster Prevention and Management: An International Journal 13*(4), 290–296.

Courtois, P. and T. Tazdaït (2007). Games of influence in climate change negotiations: Modelling interactions. *Ecological modelling 204*(3), 301–314.

de Miera, G. S., P. d. R. Gonzalez, and I. Vizcaino (2008). Analysing the impact of renewable electricity support schemes on power prices: The case of wind electricity in Spain. *Energy Policy 36*(9), 3345–3359.

de Vries, B. (2010). *Interacting with complex systems: models and games for a sustainable economy.* Netherlands Environmental Assessment Agency (PBL).

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics 4*(3), 66–95.

Dennig, F., M. B. Budolfson, M. Fleurbaey, A. Siebert, and R. H. Socolow (2015). Inequality, climate impacts on the future poor, and carbon prices. *Proceedings of the National Academy of Sciences 112*(52), 15827–15832.

Denton, M. J., S. J. Rassenti, and V. L. Smith (2001). Spot market mechanism design and competitivity issues in electric power. *Journal of Economic Behavior & Organization 44*(4), 435–453.

Dosi, G., G. Fagiolo, M. Napoletano, and A. Roventini (2013). Income distribution, credit and fiscal policies in an agent-based keynesian model. *Journal of Economic Dynamics and Control 37*(8), 1598 – 1625. Rethinking Economic Policies in a Landscape of Heterogeneous Agents.

Dosi, G., G. Fagiolo, and A. Roventini (2010). Schumpeter meeting Keynes: A policy-friendly model of endogenous growth and business cycles. *Journal of Economic Dynamics and Control 34*(9), 1748–1767.

Dosi, G. and M. Grazzi (2009). Energy, development and the environment: an appraisal three decades after the limits to growth debate. In A. Pyka, U. Cantner, A. Greiner, and T. Kuhn (Eds.), *Recent Advances in Neo-Schumpeterian Economics*. Edward Elgar.

Dosi, G. and R. R. Nelson (2010). Chapter 3 - technical change and industrial dynamics as evolutionary processes. In B. H. Hall and N. Rosenberg (Eds.), *Handbook of The Economics of Innovation, Vol. 1*, Volume 1 of *Handbook of the Economics of Innovation*, pp. 51 – 127. North-Holland.

Downing, T. E., S. Moss, and C. Pahl-Wostl (2001). Understanding climate policy using participatory agent-based social simulation. In *Multi-Agent-Based Simulation*, pp. 198–213. Springer.

Earnest, D. C. (2008). Coordination in large numbers: An agent-based model of international negotiations. *International Studies Quarterly 52*(2), 363–382.

Elliston, B., M. Diesendorf, and I. MacGill (2012). Simulations of scenarios with 100% renewable electricity in the Australian National Electricity Market. *Energy Policy 45*, 606 – 613.

Faber, A., M. Valente, and P. Janssen (2010). Exploring domestic micro-cogeneration in the Netherlands: An agent-based demand model for technology diffusion. *Energy Policy 38*(6), 2763 – 2775. The Role of Trust in Managing Uncertainties in the Transition to a Sustainable Energy Economy, Special Section with Regular Papers.

Fagiolo, G. and A. Roventini (2017). Macroeconomic policy in DSGE and agent-based models redux: New developments and challenges ahead. *Journal of Artificial Societies and Social Simulation 20*(1), 1.

Farmer, D. J. and D. Foley (2009). The economy needs agent-based modeling. *Nature 460*, 685–686.

Farmer, J. D., C. Hepburn, P. Mealy, and A. Teytelboym (2015). A third wave in the economics of climate change. *Environmental and Resource Economics 62*(2), 329–357.

Fawcett, T. (2010). Personal carbon trading: A policy ahead of its time? *Energy Policy 38*(11), 6868 – 6876. Energy Efficiency Policies and Strategies with regular papers.

Fiddaman, T. S. (1997). *Feedback complexity in integrated climate-economy models*. Ph. D. thesis, Massachusetts Institute of Technology.

Fiddaman, T. S. (2002). Exploring policy options with a behavioral climate–economy model. *System Dynamics Review 18*(2), 243–267.

Filatova, T., P. H. Verburg, D. C. Parker, and C. A. Stannard (2013). Spatial agent-based models for socio-ecological systems: Challenges and prospects. *Environmental Modelling & Software 45*, 1–7. Thematic Issue on Spatial Agent-Based Models for Socio-Ecological Systems.

Flake, G. W. (1988). *The Computational Beauty of Nature*. The MIT Press.

Forrester, J. W. (1958). Industrial dynamics: a major breakthrough for decision makers. *Harvard business review 36*(4), 37–66.

Franke, R. and F. Westerhoff (2012). Structural stochastic volatility in asset pricing dynamics: Estimation and model contest. *Journal of Economic Dynamics and Control 36*(8), 1193 – 1211. Quantifying and Understanding Dysfunctions in Financial Markets.

Frenken, K., L. Marengo, and M. Valente (1999). Interdependencies, nearly-decomposability and adaptation. In *Computational techniques for modelling learning in economics*, pp. 145–165. Springer.

Fulton, M. and M. Weber (2015). Carbon asset risk: Discussion framework. Technical report, WRI and UNEP-FI Portfolio Carbon Initiative.

Geroski, P. A. (2000). Models of technology diffusion. *Research Policy 29*(4), 603–625.

Gerst, M., P. Wang, A. Roventini, G. Fagiolo, G. Dosi, R. Howarth, and M. Borsuk (2013). Agent-based modeling of climate policy: An introduction to the ENGAGE multi-level model framework. *Environmental Modelling & Software 44*, 62 – 75. Thematic Issue on Innovative Approaches to Global Change Modelling.

Gilli, M. and P. Winker (2003). A global optimization heuristic for estimating agent based models. *Computational Statistics & Data Analysis 42*(3), 299–312.

Grazzini, J., M. Richiardi, and M. Tsionas (2015). Bayesian estimation of agent-based models. Technical Report W12, Nuffield College Economic Working Papers Series.

Greeven, S. (2015). *Society's response to climate change-A scenario discovery study using agent-based modelling.* Ph. D. thesis, TU Delft, Delft University of Technology.

Guerci, E., S. Ivaldi, and S. Cincotti (2005). Modeling and implementation of an artificial electricity market using agent-based technology. *Physica A: Statistical Mechanics and its Applications 355*(1), 69–76.

Guerci, E., S. Ivaldi, and S. Cincotti (2008). Learning agents in an artificial power exchange: Tacit collusion, market power and efficiency of two double-auction mechanisms. *Computational Economics 32*(1-2), 73–98.

Guerci, E., M. A. Rastergar, and S. Cincotti (2010). Agent-based modeling and simulation of competitive wholesale electricity markets. In *Handbook of Power Systems II*, pp. 241–286. Springer Berlin Heidelberg.

Guerci, E. and A. Sapio (2012). High wind Penetration in an Agent-Based Model of the Electricity Market. The Case of Italy. *Revue de l'OFCE 0*(5), 415–447.

Guerci, E. and S. Sapio (2011). Comparison and empirical validation of optimizing and agent-based models of the italian electricity market. In *2011 8th International Conference on the European Energy Market (EEM)*, pp. 849–856.

Guerini, M. and A. Moneta (2016, December). A Method for Agent-Based Models Validation. LEM Papers Series 2016/16, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.

Haas, A. and C. Jaeger (2005). Agents, bayes, and climatic risks-a modular modelling approach. *Advances in Geosciences 4*(4), 3–7.

Haimes, Y. and P. Jiang (2001). Leontief-based model of risk in complex interconnected infrastructures. *Journal of Infrastructure Systems 7*(1), 1–12.

Hallegatte, S. (2008). An adaptive regional input-output model and its application to the assessment of the economic cost of katrina. *Risk Analysis 28*(3), 779–799.

Hallegatte, S. (2014). Modeling the role of inventories and heterogeneity in the assessment of the economic costs of natural disasters. *Risk Analysis 34*(1), 152–167.

Hallegatte, S., N. Ranger, O. Mestre, P. Dumas, J. Corfee-Morlot, C. Herweijer, and R. M. Wood (2010). Assessing climate change impacts, sea level rise and storm surge risk in port cities: a case study on copenhagen. *Climatic Change 104*(1), 113–137.

Hasselmann, K. (2010). The climate change game. *Nature Geoscience 3*(8), 511–512.

Hasselmann, K. and D. V. Kovalevsky (2013). Simulating animal spirits in actor-based environmental models. *Environmental modelling & software 44*, 10–24.

Heitzig, J., K. Lessmann, and Y. Zou (2011). Self-enforcing strategies to deter free-riding in the climate change mitigation game and other repeated public good games. *Proceedings of the National Academy of Sciences 108*(38), 15739–15744.

Helbing, D. (2013, 05). Globally networked risks and how to respond. *Nature 497*(7447), 51–59.

Henriet, F., S. Hallegatte, and L. Tabourier (2012). Firm-network characteristics and economic robustness to natural disasters. *Journal of Economic Dynamics and Control 36*(1), 150 – 167.

Hoel, M. and K. Schneider (1997). Incentives to participate in an international environmental agreement. *Environmental and Resource economics 9*(2), 153–170.

Homer-Dixon, T., B. Walker, R. Biggs, A.-S. Crépin, C. Folke, E. F. Lambin, G. D. Peterson, J. Rockström, M. Scheffer, W. Steffen, et al. (2015). Synchronous failure: the emerging causal architecture of global crisis. *Ecology and Society 20*(3), 6.

IPCC (2014). Climate change working group III contribution to the IPCC Fifth Assessment Report. In O. Edenhofer, R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, et al. (Eds.), *Climate change 2014: Mitigation of climate change.* Cambridge (UK) and New York (US): Cambridge University Press.

Isley, S., R. Lempert, S. Popper, and R. Vardavas (2013). An evolutionary model of industry transformation and the political sustainability of emission control policies. Technical report, RAND Corporation - TR-1308-NSF.

Isley, S. C., R. J. Lempert, S. W. Popper, and R. Vardavas (2015). The effect of near-term policy choices on long-term greenhouse gas transformation pathways. *Global Environmental Change 34*, 147–158.

Jackson, J. (2010). Improving energy efficiency and smart grid program analysis with agent-based end-use forecasting models. *Energy Policy 38*(7), 3771 – 3780. Large-scale wind power in electricity markets with Regular Papers.

Jaeger, C. (2012). Scarcity and coordination in the global commons. In C. Jaeger, K. Hasselmann, G. Leipold, D. Mangalagiu, and J. D. Tàbara (Eds.), *Reframing the Problem of Climate Change: From Zero Sum Game to Win-Win Solutions*, pp. 85–101. Routledge.

Jaeger, C., K. Hasselmann, G. Leipold, D. Mangalagiu, and J. D. Tàbara (2013). *Reframing the problem of climate change: from zero sum game to win-win solutions.* Routledge.

Jaeger, C. C. and J. Jaeger (2011). Three views of two degrees. *Regional Environmental Change 11*(1), 15–26.

Jamasb, T. and M. Pollitt (2005). Electricity market reform in the European Union: review of progress toward liberalization & integration. *The Energy Journal 26*, 11–41.

Janssen, M. and B. de Vries (1998). The battle of perspectives: a multi-agent model with adaptive responses to climate change. *Ecological economics 26*(1), 43–65.

Janssen, M. and W. Jager (2002). Simulating diffusion of green products. *Journal of Evolutionary Economics 12*(3), 283–306.

Janssen, M. A. and E. Ostrom (2006). Governing social-ecological systems. *Handbook of computational economics 2*, 1465–1509.

Karpf, A., S. Battiston, and A. Mandel (2016). A network-based analysis of the EU ETS. In S. Battiston, F. D. Pellegrini, G. Caldarelli, and E. Merelli (Eds.), *Proceedings of ECCS 2014*, Springer Proceedings in Complexity. Springer.

Keith, D. (2013). *A case for climate engineering.* MIT Press.

Kelly, R. A., A. J. Jakeman, O. Barreteau, M. E. Borsuk, S. ElSawah, S. H. Hamilton, H. J. Henriksen, S. Kuikka, H. R. Maier, A. E. Rizzoli, H. van Delden, and A. A. Voinov (2013). Selecting among five common modelling approaches for integrated environmental assessment and management. *Environmental Modelling & Software 47*, 159 – 181.

Kemp, R. (2010). Eco-innovation: definition, measurement, and open research issues. *Economia Politica 27*(3), 397–420.

Kiesling, E., M. Günther, C. Stummer, and L. Wakolbinger (2012). Agent-based simulation of innovation diffusion: a review. *Central European Journal of Operations Research 20*(2), 183–230.

Knight, F. (1921). *Risk, Uncertainty, and Profits.* Chicago, Chicago University Press.

Kovalevsky, D. V. and K. Hasselmann (2014). Assessing the transition to a low-carbon economy using actor-based system-dynamic models. In A. E. R. Daniel P. Ames, Nigel W. T. Quinn (Ed.), *Proceedings of the 7th Intl. Congress on Env. Modelling and Software.*

Kowalska-Pyzalska, A., K. Maciejowska, K. Suszczyński, K. Sznajd-Weron, and R. Weron (2014). Turning green: Agent-based modeling of the adoption of dynamic electricity tariffs. *Energy Policy 72*, 164 – 174.

Kunneke, R. (2008). Institutional reform and technological practice: the case of electricity. *Industrial and Corporate Change 17*(2), 233–265.

Künneke, R., J. Groenewegen, and C. Menard (2010). Aligning modes of organization with technology: Critical transactions in the reform of infrastructures. *Journal of Economic Behavior & Organization 75*(3), 494–505.

L'Abbate, A., G. Migliavacca, R. Calisti, C. Brancucci Martinez-Anido, A. Chaouachi, and G. Fulli (2014). Regional energy initiatives in the mediterranean basin. In C. Cambini and A. Rubino (Eds.), *Regional Energy Initiatives: MedReg and the Energy Community.* London: Routledge.

Lamperti, F. (2016, 04). Empirical Validation of Simulated Models through the GSL-div: an Illustrative Application. LEM Papers Series 2016/18, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.

Lamperti, F. (2017). An information theoretic criterion for the empirical validation of simulation models. *Econometrics and Statistics*, forthcoming.

Lamperti, F., G. Dosi, M. Napoletano, A. Roventini, and A. Sapio (2016). Faraway, so close: an agent-based model for climate, energy and macroeconomic policy. LEM working papers forthcoming, Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.

Lazarus, M. and K. Tempest (2014). Fossil fuel supply, green growth, and unburnable carbon. Technical report, SEI Discussion Brief - Stockholm Environment Institute.

Lee, T., R. Yao, and P. Coker (2014). An analysis of UK policies for domestic energy reduction using an agent based tool. *Energy Policy 66*, 267 – 279.

Lempert, R., J. Scheffran, and D. F. Sprinz (2009). Methods for long-term environmental policy challenges. *Global Environmental Politics 9*(3), 106–133.

Lessmann, K., U. Kornek, V. Bosetti, R. Dellink, J. Emmerling, J. Eyckmans, M. Nagashima, H.-P. Weikard, and Z. Yang (2015). The stability and effectiveness of climate coalitions. *Environmental and Resource Economics 62*(4), 811–836.

Li, H. and L. Tesfatsion (2009, Summer). Development of open source software for power market research: the AMES test bed. *The Journal of Energy Markets 2*(2), 111–128.

Mandel, A., S. Fürst, W. Lass, F. Meissner, and C. Jaeger (2009). Lagom generic: an agent-based model of growing economies. Technical report, European Climate Forum, Working Paper 1/2009.

Markard, J., R. Raven, and B. Truffer (2012). Sustainability transitions: An emerging field of research and its prospects. *Research Policy 41*(6), 955–967.

Mastrandrea, M. D. and S. H. Schneider (2001). Integrated assessment of abrupt climatic changes. *Climate Policy 1*(4), 433–449.

Matthews, R. B., N. G. Gilbert, A. Roach, J. G. Polhill, and N. M. Gotts (2007). Agent-based land-use models: a review of applications. *Landscape Ecology 22*(10), 1447–1459.

Mazzucato, M. (2015). The (green?) entrepreneurial state. In *The Politics of Green Transformations*. Routledge.

McGinty, M. (2006). International environmental agreements among asymmetric nations. *Oxford Economic Papers 59*(1), 45–62.

Meadows, D., J. Randers, and D. Meadows (2004). *Limits to growth: The 30-year update*. Chelsea Green Publishing.

Meadows, D. H., D. L. Meadows, and J. Randers (1992). *Beyond the limits: confronting global collapse envisioning a sustainable future*. Post Mills Vermont Chelsea Green Publishing Company 1992.

Meadows, D. H., D. L. Meadows, J. Randers, and W. W. Behrens (1972). *The limits to growth*. New York: Universe Books.

Mercure, J.-F., H. Pollitt, A. M. Bassi, J. E. Viñuales, and N. R. Edwards (2016). Modelling complex systems of heterogeneous agents to better design sustainability transitions policy. *Global Environmental Change 37*, 102 – 115.

Monasterolo, I. and M. Raberto (2016). A hybrid system dynamics – agent based model to assess the role of green fiscal and monetary policies. Technical report, SSRN.

Moss, S. (2002a). Agent based modelling for integrated assessment. *Integrated Assessment 3*(1), 63–77.

Moss, S. (2002b). Policy analysis from first principles. *PNAS 99*(3), 72677274.

Moss, S., C. Pahl-Wostl, and T. Downing (2001). Agent-based integrated assessment modelling: the example of climate change. *Integrated Assessment 2*(1), 17–30.

Mureddu, M., G. Caldarelli, A. Chessa, A. Scala, and A. Damiano (2015). Green power grids: How energy from renewable sources affects networks and markets. *PloS one 10*(9), e0135312.

Narbel, P. A. (2013). What is really behind the adoption of new renewable electricity generating technologies? *Energy for Sustainable Development 17*(4), 386–390.

Nicolaisen, J., V. Petrov, and L. Tesfatsion (2001). Market power and efficiency in a computational electricity market with discriminatory double-auction pricing. *IEEE Transactions on Evolutionary Computation 5*(5), 504–523.

Nordhaus, W. et al. (2015). Climate clubs: Overcoming free-riding in international climate policy. *American Economic Review 105*(4), 1339–70.

Nordhaus, W. D. (1992). An optimal transition path for controlling greenhouse gases. *Science 258*(5086), 1315–1319.

Nordhaus, W. D. (2008). *A question of balance: economic modeling of global warming*. Yale University Press New Haven.

Okuyama, Y. (2004). Modeling spatial economic impacts of an earthquake: input-output approaches. *Disaster Prevention and Management: An International Journal 13*(4), 297–306.

Okuyama, Y. and J. R. Santos (2014). Disaster impact and input-output analysis. *Economic Systems Research 26*(1), 1–12.

Pasqualino, R., A. W. Jones, I. Monasterolo, and A. Phillips (2015). Understanding global systems today – a calibration of the World3-03 model between 1995 and 2012. *Sustainability 7*(8), 9864–9889.

Perdan, S. and A. Azapagic (2011). Carbon trading: Current schemes and future developments. *Energy Policy 39*(10), 6040 – 6054. Sustainability of biofuels.

Pindyck, R. S. (2013, September). Climate Change Policy: What Do the Models Tell Us? *Journal of Economic Literature 51*(3), 860–72.

Pizer, W. A. and D. Popp (2008). Endogenizing technological change: Matching empirical evidence to modeling needs. *Energy Economics 30*(6), 2754–2770.

Popp, D., I. Hascic, and N. Medhi (2011). Technology and the diffusion of renewable energy. *Energy Economics 33*(4), 648–662.

Putnam, R. D. (1988). Diplomacy and domestic politics: the logic of two-level games. *International organization 42*(03), 427–460.

Rassenti, S. J., V. L. Smith, and B. J. Wilson (2003). Discriminatory price auctions in electricity markets: low volatility at the expense of high price levels. *Journal of Regulatory Economics 23*(2), 109–123.

Rengs, B., M. Wackerle, A. Gazheli, M. Antal, and J. van den Bergh (2015). Testing innovation, employment and distributional impacts of climate policy packages in a macro-evolutionary systems setting. Working paper 83, WWWforEurope.

Revesz, R. L., P. H. Howard, K. Arrow, L. H. Goulder, R. E. Kopp, M. A. Livermore, M. Oppenheimer, and T. Sterner (2014). Global warming: Improve economic models of climate change. *Nature 508*(7495), 173–175.

Rezai, A. and S. Stagl (2016). Ecological macroeconomics: Introduction and review. *Ecological Economics 121*, 181–185.

Robalino, D. A. and R. J. Lempert (2000). Carrots and sticks for new technology: Abating greenhouse gas emissions in a heterogeneous and uncertain world. *Integrated Assessment 1*(1), 1–19.

Rogers, E. (1983). *Diffusion of innovations* (Third edition ed.). New York: Free Press.

Rothkopf, M. H. (1999). Daily repetition: A neglected factor in the analysis of electricity auctions. *The Electricity Journal 12*(3), 60 – 70.

Rozenberg, J., C. Guivarch, R. Lempert, and S. Hallegatte (2014). Building ssps for climate policy analysis: a scenario elicitation methodology to map the space of possible future challenges to mitigation and adaptation. *Climatic change 122*(3), 509–522.

Saguan, M., N. Keseric, P. Dessante, and J. m. Glachant (2006, Aug). Market power in power markets: Game theory vs. agent-based approach. In *2006 IEEE/PES Transmission Distribution Conference and Exposition: Latin America*, pp. 1–6.

Sapio, A. (2014). The diffusion of renewable energy technologies in the mediterranean basin. In C. Cambini and A. Rubino (Eds.), *Regional Energy Initiatives: MedReg and the Energy Community*, pp. 261–280. Routledge.

Schwoon, M. (2006). Simulating the adoption of fuel cell vehicles. *Journal of Evolutionary Economics 16*(4), 435–472.

Siegel, L. S., J. Homer, T. Fiddaman, S. McCauley, T. Franck, E. Sawin, A. P. Jones, and J. Sterman (2015). En-roads simulator reference guide.

Silverberg, G., G. Dosi, and L. Orsenigo (1988). Innovation, diversity and diffusion: a self-organisation model. *The Economic Journal 98*(393), 1032–1054.

Smajgl, A., D. G. Brown, D. Valbuena, and M. G. Huigen (2011). Empirical characterisation of agent behaviours in socio-ecological systems. *Environmental Modelling & Software 26*(7), 837 – 844.

Smead, R., R. L. Sandler, P. Forber, and J. Basl (2014). A bargaining game analysis of international climate negotiations. *Nature Climate Change 4*(6), 442–445.

Soete, L. and A. Arundel (1993). An integrated approach to european innovation and technology diffusion policy (a Maastricht memorandum). EUR(Luxembourg).

Sopha, B. M., C. A. Klöckner, and E. G. Hertwich (2011). Exploring policy options for a transition to sustainable heating system diffusion using an agent-based simulation. *Energy Policy 39*(5), 2722–2729.

Sorrell, S. and J. Sijm (2003). Carbon trading in the policy mix. *Oxford Review of Economic Policy 19*(3), 420–437.

Stanton, E. A., F. Ackerman, and S. Kartha (2009). Inside the integrated assessment models: Four issues in climate economics. *Climate and Development 1*(2), 166–184.

Sterman, J., T. Fiddaman, T. Franck, A. Jones, S. McCauley, P. Rice, E. Sawin, and L. Siegel (2012). Climate interactive: the C-ROADS climate policy model. *System Dynamics Review 28*(3), 295–305.

Sterman, J. D., T. Fiddaman, T. Franck, A. Jones, S. McCauley, P. Rice, E. Sawin, and L. Siegel (2013). Management flight simulators to support climate negotiations. *Environmental Modelling & Software 44*, 122 – 135. Thematic Issue on Innovative Approaches to Global Change Modelling.

Stern, N. (2013). The structure of economic modeling of the potential impacts of climate change: Grafting gross underestimation of risk onto already narrow science models. *Journal of Economic Literature 51*, 838–859.

Stern, N. (2016). Current climate models are grossly misleading. *Nature 530*(7591), 407–409.

Sun, J. and L. Tesfatsion (2007). Dynamic testing of wholesale power market designs: An open-source agent-based framework. *Computational Economics 30*(3), 291–327.

Tavoni, A., A. Dannenberg, G. Kallis, and A. Löschel (2011). Inequality, communication, and the avoidance of disastrous climate change in a public goods game. *Proceedings of the National Academy of Sciences 108*(29), 11825–11829.

Tesfatsion, L. (2003). Agent-based computational economics: modeling economies as complex adaptive systems. *Information Sciences 149*(4), 262–268.

Tesfatsion, L. and K. L. Judd (2006). *Handbook of computational economics: agent-based computational economics*, Volume 2. Elsevier.

Tesfatsion, L., C. R. Rehmann, D. S. Cardoso, Y. Jie, and W. J. Gutowski (2017). An agent-based platform for the study of watersheds as coupled natural and human systems. *Environmental Modelling & Software 89*, 40 – 60.

Thom, R. (1976). *Structural stability and morphogenesis.* Pergamon.

Thom, R. (1977). Structural stability, catastrophe theory, and applied mathematics. *SIAM review 19*(2), 189–201.

Tol, R. S. (1997). On the optimal control of carbon dioxide emissions: an application of fund. *Environmental Modeling & Assessment 2*(3), 151–163.

Turner, G. M. (2008). A comparison of the limits to growth with 30 years of reality. *Global Environmental Change 18*(3), 397–411.

Ventosa, M., A. Baillo, A. Ramos, and M. Rivier (2005). Electricity market modeling trends. *Energy Policy 33*(7), 897 – 913.

Vona, F. and F. Patriarca (2011). Income inequality and the development of environmental technologies. *Ecological Economics 70*(11), 2201–2213.

Voudouris, V., D. Stasinopoulos, R. Rigby, and C. D. Maio (2011). The ACEGES laboratory for energy policy: Exploring the production of crude oil. *Energy Policy 39*(9), 5480 – 5489.

Wang, J., V. Koritarov, and J.-H. Kim (2012). Cap and trade modeling in electricity markets using an agent-based approach. In P. Q. Zheng, S. Rebennack, M. P. Pardalos, F. M. V. Pereira, and A. N. Iliadis (Eds.), *Handbook of CO2 in Power Systems*, pp. 71–87. Berlin, Heidelberg: Springer Berlin Heidelberg.

Weidlich, A. and D. Veit (2008). A critical survey of agent-based wholesale electricity market models. *Energy Economics 30*(4), 1728 – 1759.

Weitzman, M. L. (2013). Tail-hedge discounting and the social cost of carbon. *Journal of Economic Literature 51*, 873–882.

Wenz, L., S. N. Willner, R. Bierkandt, and A. Levermann (2014). Acclimate—a model for economic damage propagation. part ii: a dynamic formulation of the backward effects of disaster-induced production failures in the global supply network. *Environment Systems and Decisions 34*(4), 525–539.

Windrum, P., T. Ciarli, and C. Birchenhall (2009). Consumer heterogeneity and the development of environmentallyfriendly technologies. *Technological Forecasting and Social Change 76*(4), 533–551.

Wolf, S., S. Fürst, A. Mandel, W. Lass, D. Lincke, F. Pablo-Martí, and C. Jaeger (2013). A multi-agent model of several economic regions. *Environmental modelling & software 44*, 25–43.

Zeeman, E. C. (1977). *Catastrophe theory: Selected papers, 1972–1977.* Addison-Wesley.

Zhang, B., Y. Zhang, and J. Bi (2011). An adaptive agent-based modeling approach for analyzing the influence of transaction costs on emissions trading markets. *Environmental Modelling & Software 26*(4), 482 – 491.

Zhang, H., L. Cao, and B. Zhang (2016). Emissions trading and technology adoption: An adaptive agent-based analysis of thermal power plants in China. *Resources, Conservation and Recycling forthcoming*, –.