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ORIGINAL ARTICLE

Towards agent-based integrated assessment models: examples, challenges, and future developments

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Abstract

Understanding the complex, dynamic, and non-linear relationships between human activities, the environment and the evolution of the climate is pivotal for policy design and requires appropriate tools. Despite the existence of different attempts to link the economy (or parts of it) to the evolution of the climate, results have often been disappointing and criticized. In this paper, we discuss the use of agent-based modeling for climate policy integrated assessment. First, we identify the main limitations of current mainstream models and stress how framing the problem from a complex system perspective might help, in particular when extreme climate conditions are at stake and general equilibrium effects are questionable. Second, we present two agent-based models that serve as prototypes for the analysis of coupled climate, energy, and macroeconomic dynamics. We argue that such models constitute examples of a promising approach for the integrated assessment of climate change and economic dynamics. They allow a bottom-up representation of climate damages and their cross-sectoral percolation, naturally embed distributional issues, and traditionally account for the role of finance in sustaining economic development and shaping the dynamics of energy transitions. All these issues are at the fore-front of the research in integrated assessment. Finally, we provide a careful discussion of testable policy exercises, modeling limitations, and open challenges for this stream of research. Notwithstanding great potential, there is a long way-to-go for agent-based models to catch-up with the richness of many existing integrated assessment models and overcome their major problems. This should encourage research in the area.

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Introduction

Climate change is among the major challenges mankind has ever faced. To deal with it, policymakers need timely, reliable, and accessible information about the co-evolution of the ecological and socio-economic systems. While climate scientists have made enormous progress in understanding the physical mechanisms involved in climate change, there is a lively debate on the policy relevance of existing economic models' results about how rising temperature and more frequent and catastrophic weather events might impact the economy and, more generally, the society as a whole (Burke et al. 2016; Carleton and Hsiang 2016; Stern 2016; Pindyck 2017).

The equilibrium-based integrated assessment models (IAMs), which are widely used in the literature to estimate the socio-economic losses of climate change and the social cost of carbon (SCC; e.g., IPCC 2014), have been fiercely criticized by an increasing number of scholars (among many, Ackerman et al. 2009; Pindyck 2013; Stern 2013; Weitzman 2013; Revesz et al. 2014; Farmer et al. 2015; Balint et al. 2017).[1]

While often very detailed in representing the climate and biophysical systems as well as the energy sector, when it comes to the climate-economy nexus, IAMs provide an ad hoc representation of the relationship between climate change and socio-economic damages (Ackerman et al. 2009; Pindyck 2013). Moreover, they generally underestimate uncertainty about climate dynamics and, in particular, the possibility of tipping points and non-reversibilities (Cai et al. 2015; Stern 2016).

Despite different interesting attempts (Wright and Erickson 2003), IAMs struggle to model the endogenous emergence of rare catastrophic events punctuating the evolution of the system (see also the "irregular jumps" issue in IPCC 2001). In those cases where low-probable outcomes are not overlooked a priori, IAMs tend to either impose the presence of threshold effects (Lontzek et al. 2015) or highly non-linear damage functions (Peck and Teisberg 1992). The main problem remains in the fact that these functions deterministically react to gradual changes in mean temperature values, failing to capture the effects of changes in the variability and predictability of climate conditions (Wright and Erickson 2003).

Beyond the issue of damage modeling, the most relevant weakness of IAMs pertains to their computable general equilibrium (CGE) structure. The assessment of climate change costs is performed employing a social welfare function, which is grounded on questionable assumptions about the discount rate and does not satisfactorily account for uncertainty and distributional issues. Moreover, IAMs have been developed around the concept of market equilibrium, wherein a small number of representative firms and households maximize an expected utility or profit functions and markets perfectly clear. The assumption of the representative agent is questionable on both theoretical (Kirman 1992) and empirical (Forni and Lippi 1997; Heckman 2001) grounds and prevents IAMs from studying the dynamics of income and wealth inequality related to climate change and the possible policy responses. Similarly, the straitjacket of market equilibrium does not allow to study the effects of Schumpeterian technical change, which could lead to the emergence of the radical innovations necessary to support a "green" transition.

For all the aforementioned problems, IAMs tend to underestimate the cost of climate change and the benefits resulting from the transition to a low carbon-emission economy (Stern 2016). Given the current impasse, new approaches to modeling the co-evolution of climate change and economic dynamics are needed. In recent years, agent-based, network and system-dynamics models have been increasingly advocated as possible alternatives to more standard approaches (Balbi and Giupponi 2010; Kelly et al. 2013). In that, agent-based models (Tesfatsion and Judd 2006; Fagiolo and Roventini 2012, 2017) constitute a valuable and promising approach (Smajgl et al. 2011; Farmer et al. 2015; Stern 2016; Mercure et al. 2016; Magliocca et al. 2014; Jenkins et al. 2017; Balint et al. 2017).

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

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[1] Here, 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 surveyed within the IPCC reports, despite being mostly CGE based, are employed to project socio-economic conditions under different scenarios and to assess different mitigation pathways. See Clarke et al. (2009) for an overview of these models, Emmerling et al. (2016) for a recent and detailed example, and Kriegler et al. (2015) for a policy application and multi-model comparison.

policymakers in the development of the model employed for policy evaluation (Moss 2002b).[2]

In this paper, we present a critical review of the existing literature about complex approaches to the macroeconomics of climate change, especially focusing on agent-based models (cf. "Complex systems and climate-change macroeconomics: a literature review" section). We will then present two macroeconomic agent-based models which can contribute to the integrated analysis of climate and economic dynamics and to the study of transitions towards greener production and energy systems. The LAGOM family of multi-agent models (Haas and Jaeger 2005; Mandel et al. 2009; Wolf et al. 2013a, b) is designed to represent the evolution of economic systems providing a detailed representation of production activities at the sectoral and regional levels (see "Technology, sectoral heterogeneity, and trade" section). It allows to track changes in technologies that are crucial for climate change mitigation and to explore the set of the ensuing possible economic trajectories. The Dystopian Schumpeter meeting Keynes model (DSK; Lamperti et al. 2017) studies the co-evolution between a complex economy and a climate box (see "Emissions, climate damages, and the macroeconomy" section). The DSK can be considered the first agent-based integrated assessment model allowing to study the impact of different microclimate and macroclimate shocks and the effects of alternative ensembles of policies (e.g., innovation, industrial, fiscal, and monetary policies) in fostering transitions towards a sustainable development path. The main results and complementarities between the two models will be discussed in the "Discussion" section. Finally, we will consider the open issues and future developments that macroeconomic agent-based models must face in order to provide a satisfactory integrated assessment of climate change and economic dynamics (cf. "Conclusions, open issues, and future developments" section).

Complex systems and climate-change macroeconomics: a literature review

Studying the co-evolution of climate and the macroeconomy poses non-trivial challenges. First, climate change occurs on a timescale that is longer than the available macroeconomic time series; hence, empirical explorations of the interdependencies between the two systems are difficult.[3] Second, climate damages are hard to characterize, since it requires understanding human responses to unprecedented warm climates and to extreme weather events. As we discussed in the "Introduction" section, most integrated assessment models are not satisfactory in that respect. These issues call for a re-design of how climate and weather damages are modeled (Helbing 2013), considering that due to complexity, aggregate climate impacts cannot be reduced to the simple aggregation of microeconomic impacts.

This given, one of the main advantages of macro ABM is to allow for a microlevel representation of the interactions between climate change and economic dynamics (see, e.g., Moss 2002a; Farmer et al. 2015; Balint et al. 2017). Indeed, the agent-based approach can better account for the out-of-equilibrium dynamics shifting the economy from a business-as-usual scenario to a green growth path. Macroeconomic ABMs have blossomed in recent years, and with them a new generation of agent-based integrated assessment models (Lamperti et al. 2017), whose contributions are reviewed as follows (see Balint et al. 2017, for a detailed survey on complexity and the economics of climate change).

The first complexity-based models employed to study climate change are System Dynamics (SD) models, originating from the pioneering work by Forrester (1958). The "World3" model published in Meadows et al. (1972) provided the first skeleton of the subsequent SD models.[4] A SD model comprises a stock flow-consistent dynamical system embedding three main elements: sources of amplification, time lags, and reinforcing and balancing feedback loops. Much alike ABMs, SD models employ computer simulations to explore the behavior of highly non-linear systems they allow one to study out-of-equilibrium dynamics. However, unlike ABMs, in their early instances, they only employed aggregate equations, without explicitly modeling agent-level decisions.[5] Moreover, despite accounting for feedback loops, non-smooth aggregate behavior, and multiple equilibria, microeconomic assumptions in SD models have often been in line with the standard CGE framework. One instance is given by the MADIAMS model family, a multi-actor SD-based integrated assessment model for climate policy analysis (Hasselmann 2010), that assumes agent homogeneity and utility maximizing behavior within each module (see also Hasselmann and Kovalevsky 2013; Kovalevsky and Hasselmann 2014). Fiddaman (1997) is among the first SD models for the integrated assessment of climate change, allowing for tipping points and non-linear dynamics within the climate system.

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[2] ABM have limitations as well. In particular, they are rather difficult to parameterize and validate. In addition, they are computationally intensive and they are prone to over-complexity that could make it difficult for modelers to understand agents' response and models' results. They also require more robust statistical validation tools, although important steps have recently been made (see, e.g., Fagiolo et al. 2017; Lamperti 2017a, b; Guerini and Moneta 2017; Cirillo and Gallegati 2012).

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

[4] Despite having been often misunderstood, the results of World3 simulations are still partially valid today. See Pasqualino et al. (2015) for a recent recalibration of World3.

[5] Recent works have started to address the lack of flexibility of SD models to represent micro-level behavior by introducing sectors characterized by a representative agent with a specific behavioral function, see, e.g., Monasterolo and Raberto (2018). A blossoming literature on hybrid SD-ABM is exemplified by Monasterolo et al. (2014).

Follow-ups assessing climate policies include Mastrandrea and Schneider (2001), Fiddaman (2002), Sterman et al. (2012, 2013), Akhtar et al. (2013), and Siegel et al. (2015). The cross-fertilization between SDs and ABMs might be extremely productive as it allows to gradually take account of heterogeneity, network structures, and boundedly rational behaviors, as well as to identify how non-standard assumptions impact on macrolevel phenomena (e.g., likelihood of green transition or emissions' growth rates). In the ESM, we report a systematic comparison of "CGE-based" models, ABM, and SD approaches, highlighting in more details their strengths and weaknesses both in modeling and policy-testing terms (for a similar exercise, see also Kelly et al. 2013; de Vries 2010).

One of the main advantages of SD and ABMs vis-à-vis "traditional" IAMs is their capability of accounting for system connectivity. Indeed, IAMs ignore the propagation of shocks and climate damages across interconnected sectors.[6] Moreover, as most IAMs do not assume agent heterogeneity, they entirely overlook the distributional issues linked to climate damages. Conversely, models in the complex system approach account for the emergence of aggregate damages from microshocks in production, procurement, or finance, percolating along network structures where households, firms, banks, and the government interact. For instance, the model developed by Hallegatte (2008) has studied the propagation of shocks in Louisiana after hurricane Katrina (see also Hallegatte et al. 2010; Hallegatte 2014, for extensions focused on the role of inventories in the adaptation to extreme climate events). The relationship between the topology of the production network and the resilience to natural disasters has been analyzed in Henriet et al. (2012). Moving from a relatively restricted geographical focus, Bierkandt et al. (2014) develop a model nesting agent-based features (consumption and production sites are treated as agents) in an input-output network that allows to track flows of goods in the global supply chain. The model yields a novel understanding shock propagation and the difference between top-down cascades promoted by forward linkages and by demand-induced backward dynamics (Wenz et al. 2014).

Long-run macroeconomic dynamics is beyond the horizon of the aforementioned models, as they run at higher time frequencies in which price adjustments and technical change can be assumed away. Yet those works, while limited in scope, outline the microeconomic backbone from which a realistic macroeconomic dynamics can emerge. A seminal contribution in studying the transition of the macroeconomy towards a low-carbon growth path is Robalino and Lempert (2000, see also Brouwers et al. 2001), who test, through an ABM, the effectiveness of incentives to technology adoption vis-à-vis carbon taxes and emission trading. They find that coupling carbon taxes and technology incentives is the best approach to cut greenhouse gas emissions.[7] Notwithstanding these interesting insights, the model is too simple to account for multiple equilibria and endogenous growth. In the presence of multiple equilibria, the mitigation problem is not linked to scarcity but rather to a coordination issue (Jaeger 2012). More generally, policymakers should re-frame the problem of climate change from a zero-sum game to a win-win situation, in which climate change can be mitigated while stimulating the economy (Jaeger et al. 2013). In that respect, one of the first attempts to explore coordination issues in climate policy within a complexity modeling framework can be traced back to the LAGOM model family (Haas and Jaeger 2005; Mandel et al. 2009; Wolf et al. 2013b), to be presented in the "Technology, sectoral heterogeneity, and trade" section.

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

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

The contributions described so far do not consider the feedback that agents (firms, energy generation plants, households, etc.) receive from increasing and possibly more volatile temperatures due to climate change. Isley et al. (2013) draws on the baseline setting provided by Dosi et al. (2010) to build a hybrid agent-based IAM. The authors underline the usefulness

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[6] Indeed, IAMs lack an explicit representation of climate change risks to the different types of business and financial actors, and do not include a financial sector. Therefore, these models are not fit for analyzing how climate change affects macroeconomic and financial stability, nor the effects on systemic risk formation and wealth concentration, which are highly relevant topics in the climate-finance arena (see, e.g., Carney 2016; Monasterolo et al. 2016).

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

of the approach in analyzing transformative solutions, that is, how measures to reduce GHG emissions can trigger market-induced transformations which in turn affect the ability to maintain the climate policy. However, damages are linked to emissions, not to the dynamics of temperature, and are modeled like in standard IAMs as aggregate cuts to potential GDP levels (see, e.g., Nordhaus 1992, 2008; Tol 1997).[8]

Despite the methodological advantages that ABMs offer to the representation of production networks, the study of system resilience, and its reaction to different kind of shocks, there have been little efforts in employing these tools to investigate the effects of climate change on the aggregate economy.[9] The DSK model (Lamperti et al. 2017) presented in the "Emissions, climate damages, and the macroeconomy" section is to our knowledge one of the first attempts to bridge a fully fledged agent-based model with a representation of climate-economic feedback represented as stochastic microeconomic shocks, whose probability and magnitude depend on the dynamics of the global mean surface temperature.

The DSK and the LAGOM models will be described and compared in the next sections. They can be employed as prototypes towards the integrated analysis of climate and economic dynamics, as well as for the study of transitions towards greener production and energy systems from a macroeconomic perspective. While LAGOM focuses more on the role of input-output relationships, technology, and trade, DSK offers an integrated assessment of climate dynamics and economic impacts.

Technology, sectoral heterogeneity, and trade

The LAGOM family of models (Haas and Jaeger 2005; Mandel et al. 2009; Wolf et al. 2013b) aims to overcome two shortcomings of existing IAMs based on general equilibrium: the assumption that the economy has a single equilibrium and, correlatively, the absence of any representation of out-of-equilibrium dynamics or coordination between agents. In this setting, climate policy can only induce a deviation from the "optimal" business-as-usual scenario and hence a cost to society.[10] Considering multiple equilibria and the transition between those allows to re-frame climate policy as a problem of coordination on a different equilibrium.

Implementing this alternative perspective requires the introduction of heterogeneous agents (the uniqueness of equilibrium is closely linked to the representative agent paradigm; see Sonnenschein 1972) and the replacement of the dynamic programming approach used in general equilibrium models, which pinpoints the equilibrium path without exploring the phase space of the model. Meanwhile, LAGOM aims at providing a level of sectoral granularity comparable with this of general equilibrium IAMs in order to track technological changes induced by climate policy and, from a more technical point-of-view, to provide a mapping with input-output tables.

The model

In order to achieve these dual objectives, the model (extensively described in Mandel et al. 2009) equips the standard Arrow-Debreu general equilibrium framework with agent-based dynamics. Namely, it considers an economy in discrete time, an arbitrary number of commodities, and one kind of labor. The usage of commodities is not, a priori, specialized: each can potentially be used as fixed capital, as intermediary consumption or for final consumption. The economy is populated by a finite number of firms and households, a government and a financial system. The household provides labor and consumes (non-durable) commodities. The firms are partitioned into sectors according to the goods they produce using heterogenous capital and labor. The government levies an income tax and provides unemployment insurance. The financial system sets the interest rate according to a Taylor rule, collects savings from households, and grants credit to firms for investment (see Figure 1).

Trading of goods and labor between households and firms are organized through bilateral interactions and random queuing mechanisms as in Gintis (2006, 2007). As far as behavior is concerned, agents adjust their strategies on the basis of adaptive expectations while production technologies and preferences are updated according to evolutionary mechanisms.

Projections and model dynamics

The macroeconomic dynamics that emerge from the microlevel interactions implemented in the model reproduce key features of empirical dynamics: exponential growth in the long run with business cycle fluctuations. The key macroeconomic driver of these short-term fluctuations is investment,

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[8] Much research remains to be done on the financing of low-carbon transition. Different types of green fiscal (carbon tax, tax relief, and breaks on investment in renewables) and targeted monetary policies (green bonds and quantitative easing) are simulated in the Eirin model (Monasterolo and Raberto 2018), which combines SD and ABM features. The structure of the relationships among financial institutions might also be crucial for the stability of the whole system in the face of climate change. Battiston et al. (2017) use a macro-network stress testing model (Battiston et al. 2012; Bardoscia et al. 2015) and find that the direct exposure to fossil fuel and energy-intensive sectors, while limited overall, is relevant for investment funds, which in turn are highly connected with the banking system.

[9] 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. The interested reader might also want to look at Guha-Sapir and Santos (2013) and Kousky (2014) for a critical discussion of impact-assessment and modeling practices in the context of natural disasters.

[10] As explained in Haas and Jaeger (2005), LAGOM is a Swedish word denoting a sense of balance and harmony, perhaps akin to the Chinese "Tao." This inspired the authors when choosing a name for their model.

which is much more volatile than output and consumption (see supplementary materials).

More generally, investment is in the model the central channel through which firm behaviors affect macroeconomic growth. In contrast to general equilibrium IAMs where the investment decision of (representative) firms is the outcome of an optimal choice of a central planner in view of maximizing the welfare of a representative household, in LAGOM, investment decision is the outcome of firms' adaptive expectations about the profitability of new fixed capital. As in a Keynesian beauty contest, these expectations influence the actual macroeconomic outcomes. Figure in supplementary material highlights this relationship by illustrating how the long-term growth rate, as well as the volatility, of the economy increases when expectations are updated more aggressively by the firms.

The model can also be used to assess the impacts of policies that target more directly expectations or aggregate demand. In particular, in the context of climate policies, the model could be used to assess the impacts of green stimulus plans and/or large public investments in transport or energy infrastructures. As underlined by the emphasis put on the "Juncker Investment Plan," such policies are of particular concern in Europe where investments are at a record low: although the investment rate remained relatively stable around 25% of GDP at the global scale, it fell from 30 to 20% in the European Union in the past 40 years while increasing by 10% in China.[11]

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

Extension: the regional version

The model has been extended with a spatial version, LAGOM regiO (see Wolf et al. 2013b), which divides the economic area under consideration into regions. The number of regions can be chosen by the model user, so that analyses at different geographical granularity are supported.

Each agent is located in a region at the initialization of the model. Agent strategies may vary across regions. While firms remain in their regions, households may migrate. Interaction and social learning processes occur as an agent obtains information about other agents belonging to the same region with a larger probability. This mechanism favors local interactions within regions over those between regions. Also, mutations of strategies occurring in a region are spread more easily within the region than across region boundaries.

Such a framework offers a good starting point to move from global-level models towards regional ones, allowing to mimic what happened for CGE-based integrated assessment models (e.g., from DICE to RICE).[12] In addition, it would provide a realistic and fine-grained account of cross-regional dependences, particularly in terms of technological development, trade, and labor flows.

Emissions, climate damages, and the macroeconomy

The DSK model captures the co-evolution between a complex economy and a climate box (more details on the model can be found in Lamperti et al. 2017). The two domains are linked via non-linear and stochastic feedback. As already mentioned in the "Complex systems and climate-change macroeconomics: a literature review" section, the DSK can be considered as the first agent-based integrated assessment model that can be employed to provide a detailed characterization of the different microclimate and macroclimate shocks hitting the economy. The model allows to study alternative ensembles of macroeconomic policies (e.g., innovation, industrial, fiscal, and monetary policies) that can mitigate the impact of climate change, and sustain the low-carbon transition (Fig. 1).

The model

The DSK model builds on Dosi et al. (2010, 2013) and is composed by two vertically separated industrial sectors, whose firms are fueled by an energy sector.[13] A graphical representation of the model structure is provided in Fig. 2.

In the capital-good industry, firms produce machine tools using labor and energy. Firms innovate and imitate in order to increase labor productivity, energy efficiency, and the environmental friendliness of the machines they sell to the consumption-good firms, as well as to reduce their own production costs. However, innovation and imitation are costly processes and firms invest a fraction of their past revenues in R&D activities.[14]

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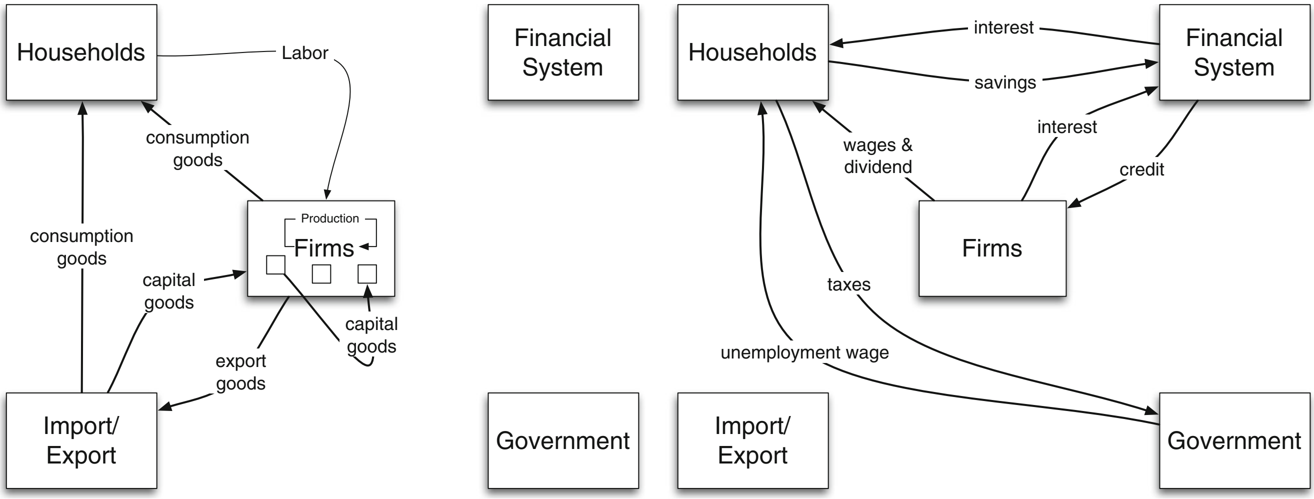
[11] See, e.g. http://data.worldbank.org/ for relevant data in this respect.

[12] Information on RICE and references to the first versions of DICE can be found in Nordhaus and Yang (1996).

[13] Other contributions belonging to the so-called K + S family include Dosi et al. (2015, 2017) and Dosi et al. (2016).

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



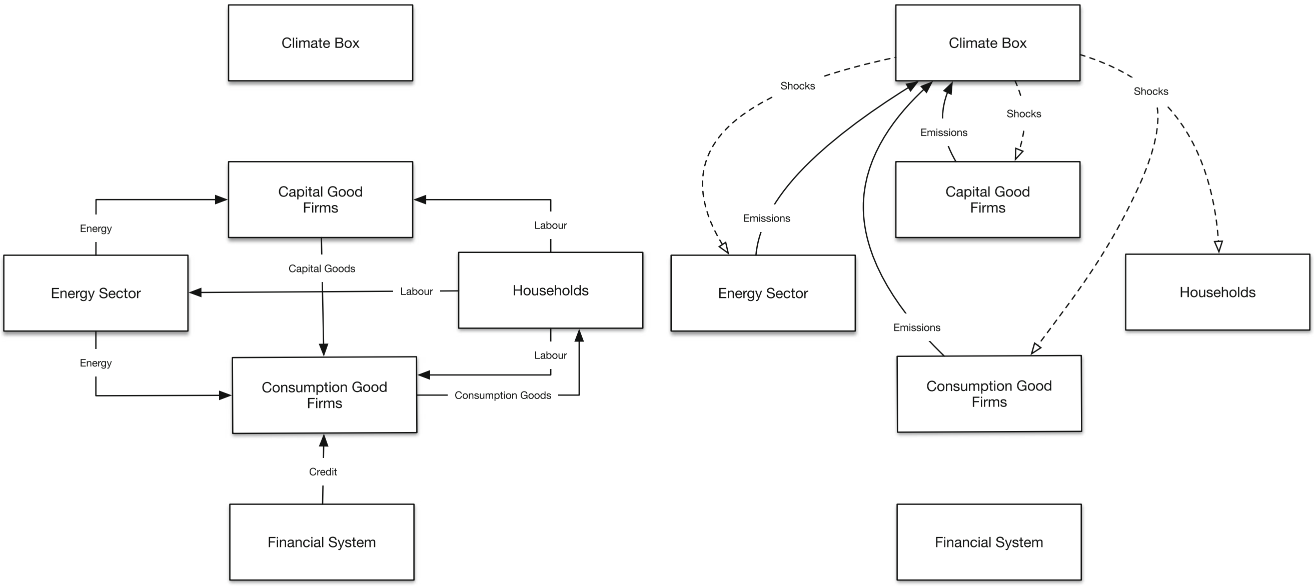
(a) Commodity flows in the LAGOM model.

(b) Financial flows in the LAGOM model.

Fig. 1 Schematic representation of the LAGOM model

Consumption-good firms invest in machines, which are employed together with labor to produce a homogenous good. Firms must finance their operations in imperfect capital markets (Stiglitz and Weiss 1981; Greenwald and Stiglitz 1993), accessing firstly their net worth and if the latter does not fully cover total production and investment costs, they borrow external funds from the bank.

Energy generation is performed by a profit-seeking, vertically integrated monopolist through heterogeneous power plants using green and dirty technologies. The energy monopolist produces and sells electricity to firms in the capital-good and consumption-good industries using a portfolio of power plants, which are heterogeneous in terms of cost structures, thermal efficiencies, and environmental impact. "Green" plants convert renewable energy sources into electrical power at a null marginal production cost and produce no greenhouse gas emissions. However, large fixed costs are necessary to build up new green plants. Conversely, the stock of fossil-fueled plants can be expanded at virtually zero fixed costs, but energy generation via dirty power plants involves positive marginal costs reflecting the



(a) Economic flows in the DSK model.

(b) Climate-related flows in the DSK.

Fig. 2 Schematic representation of the DSK model price of fossil fuels. Technical change occurs along both the technological trajectories (green and dirty; see Dosi 1988) and improves plants' efficiency and environmental friendliness.

Finally, a climate box links CO_2 emissions, generated by both the energy and industrial sectors, with atmospheric carbon concentrations and the ensuing dynamics of the Earth's mean surface temperature. These relationships are modeled in a non-linear way through a core carbon cycle characterized by feedback as in Sterman et al. (2012, 2013). In particular, our carbon cycle is modeled as a one-dimensional compartment box based on Goudriaan and Ketner (1984) and Oeschger et al. (1975), capturing feedback that might give rise to non-linear dynamics. Atmospheric CO_2 is determined on a yearly basis by the interplay of different factors, which account for anthropogenic emissions, exchanges of carbon dioxide with the oceans, and net primary production.

The effects of an increase in the Earth's temperature on the economic system are captured by a stochastic disaster-generating function. The disaster-generating function changes over time according to temperature dynamics: under a warming climate, the probability of larger microeconomic shocks in labor productivity and firms' capital stock increases together with the mean size of the damage. Therefore, an increase in the Earth's surface temperature does not translate automatically in higher aggregate damages as in most IAMs; rather, it modifies at the microlevel the structure of the stochastic process characterizing economic growth.

Projections and model dynamics

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

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

Both issues involve the short- and long-run dynamics of the model. The raising temperature stemming from increasing emissions can lead to stronger and more volatile climate shocks, which may induce downturns and crises, possibly hampering the growth performance of the economy. The transition from a dirty to a green economy can depend on business cycle conditions, but in turn can also affect potential output growth. Hence, in presence of climate change, the plea of Solow (2005) for macroeconomic models able to jointly account short-and long-run dynamics is even more relevant.[15] The ability of the DSK model to simultaneously account for short- and long-run features (see Lamperti et al. 2017, for details) is, in our opinion, a key aspect of the overall exercise and a major advantage over standard IAMs.[16]

Let us now explore the dynamics of the DSK model in the benchmark, business-as-usual (BAU) scenario, where the model is calibrated and initialized on the main features of the global economy in year 2000, climate shocks are switched off, and no climate policy is introduced.[17] The simulation protocol is simple: we run the model for 400 periods, which are to be interpreted as quarters, thereby obtaining projections until year 2100. The model, similarly to LAGOM ("Technology, sectoral heterogeneity, and trade" section), generates multiple possible trajectories, each linked to a different pattern of technical change in the industrial and energy sectors. Moreover, since the model is stochastic, we rely on Monte Carlo (MC) experiments to wash away patterns due to specific realizations. Figure in supplementary materials shows a representative run for three quantities of interest, while MC averages and standard deviations for the main macroeconomic and climate-related variables are collected in Table 1.

We robustly find endogenous growth of output and energy demand, which increase at similar rates. Emissions steadily grow as well, but at a lower pace, in line with recent evidence collected in Olivier et al. (2015). Unemployment rates seem to be quite stable across runs and in accordance with actual data for some countries.[18] Moreover, projections indicate that the economic system grows with endogenous fluctuations punctuated by major crises (see, e.g., NBER 2010; Claessens and Kose 2013). Finally, simulation results show that the share of renewable energy in total energy production exhibits an average of 30% over the whole time span (2000–2010) and it is higher than 20% only in one third of the periods, thus indicating that transitions towards a green economy in a business-as-usual scenario are quite unlikely.[19]

Beyond these macroeconomic features, the DSK model reproduces various microlevel stylized facts concerning industrial and energy system dynamics. Firms display persistent differentials in their productivity (in line with Bartelsman and Doms 2000), energy, and carbon efficiency (in accordance with DeCanio

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

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

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

[18] See World Bank, WDI: http://wdi.worldbank.org/table/2.5.

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

Table 1 Summary statistics on selected variables under BAU and no climate damages in the DSK model

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

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

and Watkins 1998 and Petrick 2013); the distribution of firm growth rates exhibits fat tails (see, e.g., Bottazzi and Secchi 2006); and the firm size distribution is right skewed.

Let us now consider the dynamics of temperature. Figure 3 shows it along the whole time span for each of the Monte Carlo runs and reports their distribution at the middle and final point of the simulation. The results are relatively aligned with those produced by the most widely used IAMs (Nordhaus 2014), but some remarkable differences exist. First, our average temperature projections are higher than in many other models (see Clarke et al. 2009; Gillingham et al. 2015), supporting a rather pessimistic view of the BAU scenario. Second, the evolution of temperature exhibits a peculiar dynamics, which we did not observe in other contributions. In particular, a first phase of gradual increase is followed by a period (indicatively located between 2025 and 2050) when climate change accelerates dramatically, before reaching a nearly constant growth in a third phase. Such dynamics, which is driven by the feedback mechanisms characterizing the carbon cycle (see Sterman et al. 2013), call for urgent policy interventions.[20] Finally, Fig. 3b shows the MC distribution of temperature at the middle (2050) and final (2100) simulation steps. Being the model stochastic only in the search for innovations (climate shocks are switched off), such distributions characterize the uncertainty surrounding climate change stemming from technical change (Dosi 1988). Across time, the mean, the support, and the tails of the temperature distribution increase, suggesting the non-linear accelerating dynamics of climate change.

Discussion

The two agent-based models introduced above offer novel perspectives with respect to computable general equilibrium IAMs for the analysis of coupled climate-economic dynamics. In what follows, we briefly discuss the areas where the two models provide major contributions: climate-economy feedback and policy implementation. We then discuss the potential to build broader modular agent-based models on the basis of the DSK and LAGOM frameworks.

Climate-economy feedback

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

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

As already mentioned in the "Complex systems and climate-change macroeconomics: a literature review" section, agent-based integrated assessment models allow disaggregated climate and weather shocks and, therefore, avoid the aggregation problems faced in traditional modeling frameworks (Fankhauser et al. 1997; Anthoff

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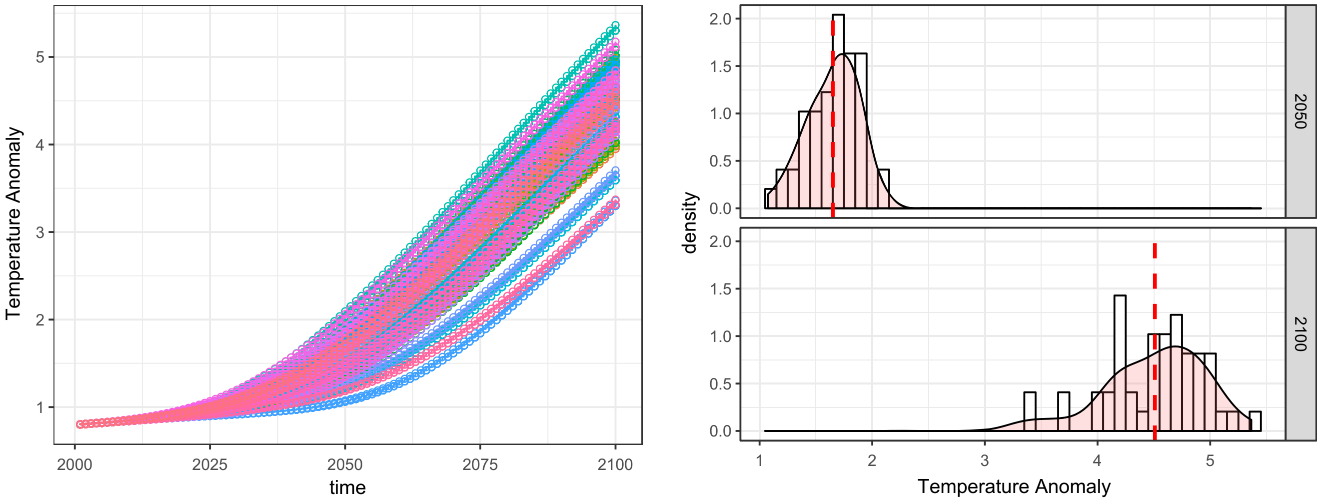
[20] The carbon cycle feedback exert a relatively greater effect when the state variables in the climate box move away from the assumed pre-industrial equilibrium, while their effects becomes less important (relatively to the same change in the state variables) when climate change becomes aggressive.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



(a) Temperature projections. (b) Distribution of temperature.

Fig. 3 Temperature projections and their density estimates from the DSK model. Both graphs refer to a Monte Carlo of size 50. Red dashed lines in **b** indicate mean values

and Tol 2010).[21] Unlike standard IAMs, agent-based integrated assessment models allow to study a variety of different climate change impacts, ranging from capital destruction and productivity losses to reductions in labor force participation and workers' health (see Lamperti et al. 2017). Moreover, each agent in the system can be directly hit by a random climate shock with a probability that depends on the dynamics of temperature. Similarly, the size of the shock is dynamically affected by climate change. Indirect effects of climate shocks take place via the economic networks each agent is embedded in. This framework yields endogenously generated catastrophic events, while leaving the modeler with larger degrees of freedom (e.g., the choice of the probability distribution from which climate shocks are sampled and the link between temperature's dynamics and the probability function). In that, Lamperti et al. (2017) propose to explore a variety of combinations of impacts and density specifications in order to build a novel set of socio-economic scenarios, each characterized by different shocks' targets, intensity of climate damages, and macroeconomic performances. Figure 4 provides an illustrative example of two different cases obtained through the DSK model. In particular, it shows the dynamics of output when climate shocks target labor productivity (in Fig. 4a) and firms' inventories (in Fig. 4b). The stark difference between the two (a stagnating, no-growth regime vs. high frequency of crises and large fluctuations accompanied by relatively sustained growth) call for better qualifying how climate change impacts an economic system and the ecology of agents.

Policy implementation

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

Remarkably, the two models allow for a wide a range of policy exercises that go beyond the mere introduction of carbon taxes. Furthermore, they highlight the distributional impacts of the coupled climate-economy dynamics and of policy interventions, even within given categories of agents (see also Farmer et al. 2015). Table 2 provides a non-exhaustive list of the various policies that can be tested with LAGOM and DSK models. The flexibility and modularity of ABMs (Fagiolo and Roventini 2012, 2017; Balint et al. 2017) allow to study how different policy combinations can promote the low-carbon transition. Finally, the observable economic structure and climate dynamics and the higher degree of realism of the

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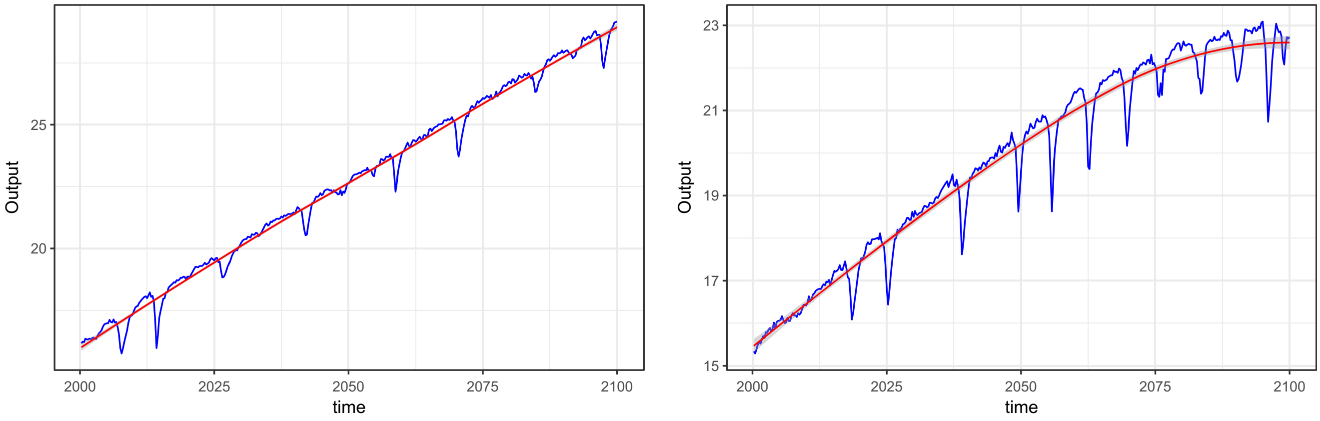
[21] To the best of the authors' knowledge, Tol (1997) provides the only IAM allowing for sector-specific climate damages, but it does not allow for agent specific shocks and does not explain how sectoral damages emerge (e.g., productivity loss, efficiency loss, capital stock loss). There are also different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



(a) Output dynamics under inventories shocks.

(b) Output dynamics under labour productivity shocks.

Fig. 4 Behavior of real output in two different climate shock scenarios as projected by the DSK model; output is measured in units of final good

LAGOM and DSK models facilitate the interactions with policymakers and stakeholders in policy co-design (Moss 2002b).

Towards a modular structure

In order to take advantage of the complementarity emphasized above, the modularity and inter-operability of models should be increased. The climate box connected to the DSK model is a promising step in this respect. Indeed, this DSK module could be interfaced with LAGOM and the distribution of climate-related shocks induced in DSK could be used in LAGOM. Conversely, the consumption-good sector of the DSK model could be disaggregated using a LAGOM-like structure, in particular to account for intermediary consumption. These potential linkages are not restricted to the two models presented here. In order to take full advantage of the potential synergies between ABMs focusing on macroeconomic dynamics, the structure of production networks, sector-specific dynamics, or the energy-environment nexus, a number of milestones seem necessary: a shared protocol for model specification (Wolf et al. 2013a, as in), a platform for a standardized implementation of the different models, a modular structuring of future versions of the models, and interfaces that allow for simple and efficient linkages between models focusing on different dimensions of the climate-economy nexus.

The prospective construction of a modular, publicly available agent-based platform would replicate, in terms of model development, the successful experience of the DICE-RICE model family (Nordhaus 1992; Nordhaus and Yang 1996; Nordhaus 2008). However, it will provide a completely different, yet more realistic, tool for climate impact analysis and policy testing. In some respect, DSK and DICE are already comparable. DSK can be seen as the agent-based counterpart of what DICE had been: a pioneering attempt to provide a simple global-level integrated assessment model. What differs is the foundational structure of the economic system. The introduction of heterogeneity, bounded rationality, and network relationships results in completely different dynamics and climate damages. For example, under the same "business-as-usual" emission scenario, roughly adherent to the Representative Concentration Pathway (RCP) 8.5, the average climate shock from DSK and the damage function in DICE2013r (Nordhaus 2014) are vaguely similar: the 2100-μ-level shock averages 5.4% while the DICE damage function

Table 2 Policy exercises available in the LAGOM and DSK models

Climate and energy policy	Macropolicy DSK	Industrial policy
Carbon tax	Fiscal policy	Standards
Command and control	Green quantitative easing	Reforms to the patent system
Fossil fuel taxes	Green bonds	
Minimum share of renewable energy		
LAGOM		
Energy taxes and subsidies	Labor market policies	
Coordination of investments	Monetary policy	
Expectation management		

implies a GDP loss of approximately 5.2%. However, aggregate impacts are radically different, with end-of-century projected output being around 90% of the "without-climate-change" scenario in DICE while amounting to 15% in DSK (with shocks assumed to target labor productivity). Even though further and more detailed comparisons will be performed in future research, preliminary evidence shows that climate impacts vividly increase as more realistic assumption about the structure of the economy are introduced.

Conclusions, open issues, and future developments

In this paper, we have argued that ABM is a most promising approach to the integrated assessment of climate change and economic dynamics. ABMs aim to overcome the limitations of the existing IAMs, which are typically nested in a representative-agent computable general equilibrium framework (simplistic representation of CO_2 concentration and temperature increases, neglect of large catastrophes, tipping points and irreversibilities in climate change dynamics, ad hoc hypotheses concerning the shape of the social welfare function and discount rates, etc.).[22]

In the ABMs outlined in this paper, the economy is a complex evolving system populated by heterogeneous and locally interacting agents, and the macroeconomic effects of climate change are more adequately characterized as emergent properties of such complex dynamics. As such, they cannot be reduced to the decisions of a representative individual. Moreover, the heterogeneity of agents allows for a systematic analysis of the distributional impacts of climate change. Finally, ABMs are more flexible than standard IAMs, providing more realistic representations of damage functions, of the institutional processes shaping climate policies, and of technical change governing the appearance, evolution, and demise of dirty and clean technologies.

We have then illustrated two families of ABMs, namely, LAGOM and DSK, and we have explored their main differences and complementarities. The DSK model offers a complete characterization of the feedback between climate and the economy. This offers a detailed analysis of how various types of climate shocks affects growth and of the economic policies that can foster the transition to a sustainable path. The climate-economy interplay is represented in a much lower detail in LAGOM, which however guarantees a more fine-grained representation of the multi-sectoral and spatial dynamics of the economy. Accordingly, LAGOM can be used to study how climate shocks propagate through the production network and to identify the nodes that are crucial for the resilience of the system.

Complexity-based approaches represent a promising route towards more informative and reliable analyses of the climate-economy co-evolution (see also Farmer et al. 2015; Balint et al. 2017). Nevertheless, understanding the aggregate economic effects of climate change is still limited, and there is large room for improvement. Further, we acknowledge that current ABMs should be developed to account for elements (e.g., fine-grained representation of the energy system, land use, and cover change processes) that are yet present in many computable general equilibrium-based IAMs. Beyond such extensions, there are (at least) three main issues that future advancements should account from a macroeconomic perspective.

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

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

Finally, the major open question for integrated assessment modeling probably consists in the development and application of credible and empirically robust damage functions. In agent-based models like those described in "Technology, sectoral heterogeneity, and trade" and "Emissions, climate damages, and the macroeconomy" sections, climate damages take the form of stochastic shocks sampled from time-varying distributions. Although such damage functions constitute an improvement with respect to those used in standard IAMs, they might still be considered arbitrary (see the discussion in Pindyck 2013). The literature on disaster risk and insurance (Dilley et al.2005; Li et al. 2013; Michel-Kerjan et al. 2013; Bouwer 2013; Hallegatte 2014) might provide empirically sound distributions for different weather and climate change-related events (e.g., capital stock loss due to a tsunami) that

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[22] The interest reader may find a systematic comparison of different modeling approaches to integrated assessment within the supplementary online materials.

flexible ABMs might proxy.[23] Taking this opportunity into account would, in our opinion, help to address various critiques that damage functions usually receive.

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

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