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PERSPECTIVE

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Agent-based modeling to integrate elements from different disciplines for ambitious climate policy

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Abstract

Ambitious climate mitigation policies face social and political resistance. One reason is that existing policies insufficiently capture the diversity of relevant insights from the social sciences about potential policy outcomes. We argue that agent-based models can serve as a powerful tool for integration of elements from different disciplines. Having such a common platform will enable a more complete assessment of climate policies, in terms of criteria like effectiveness, equity and public support.

This article is categorized under:

Climate Models and Modeling > Knowledge Generation with Models
The Carbon Economy and Climate Mitigation > Policies, Instruments, Lifestyles, Behavior
Policy and Governance > Multilevel and Transnational Climate Change Governance

KEYWORDS

agent-based modelling, climate change, policy acceptability, policy integration, policy stringency

1 | INTRODUCTION

Stringent policies needed to avoid dangerous climate change have turned out to be difficult to implement, primarily due to considerable social and political resistance (Klenert et al., 2018). This is demonstrated by, among others, general election victories created partly by repealing of carbon pricing in Australia (Crowley, 2017), two public referenda rejecting an initiative to introduce a carbon tax in the State of Washington (Reed et al., 2019) and social movements such as the Yellow Vest protests in France against a fuel tax with a carbon component (Douenne & Fabre, 2020). While in Australia resistance was led by fossil fuel lobby, in the US and France high perceived cost of the policy and potential regressive effects drove negative attitudes of the general public. Other climate policy instruments, such as subsidies in renewable energy, fuel emission standards and road tolls, also have seen public resistance (Aasen & Sælen, 2022; Benegal & Holman, 2021; Stokes, 2016).

To overcome such resistance, we need to better understand consequences of such policies. While there are currently many models for assessing environmental, social and economic impacts of climate policy, the majority of these suffer from disciplinary bias. Illustrative of this are: a narrow operationalization of rational agents in economic equilibrium models; scarce attention for the role of companies and cross-sectoral linkages in psychological and sociological studies; and limited understanding of the power of vested interests (Farmer et al., 2015; Stern, 2016). Such biases can result in overlooking important policy impacts, which complicates a balanced evaluation of all relevant criteria—such as effectiveness, efficiency, equity and acceptability. In turn, this may weaken social and political support for climate policy (Sarewitz, 2011).

To achieve a careful comparison of climate policy instruments, we suggest integrating elements from different social sciences—notably psychology, sociology, economics and political science (Figure 1). These elements may involve concepts, mechanisms, indicators, and policy instruments that are the focus of particular disciplines. Accounting for these will contribute to a more complete perspective on potential policy implications as well as recognize and value differences between disciplines on how to design ambitious climate policy (Klenk & Meehan, 2015). In this article we argue that agent-based models (ABMs) form an appropriate tool to enable such an integration and compare their performance with alternative modeling approaches. Several earlier studies acknowledge the potential role of ABMs for such an integration task. For instance, Adger et al. (2013) argue that they "integrate traditional and scientific perspectives on change [...] to specifically support the design of adaptive management systems [for climate change adaptation]".

2 | WHY SPECIFICALLY AGENT-BASED MODELING?

ABMs are a type of computational models used to simulate the behavior of autonomous agents—such as, households, firms, or entire countries—to derive aggregate outcomes from the interaction of its constituent parts. Being formalized

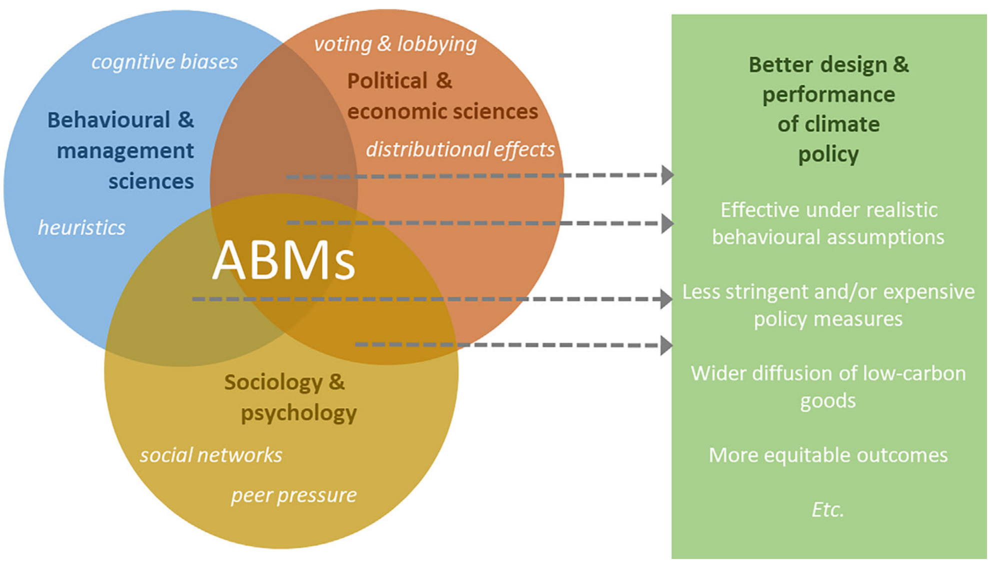

FIGURE 1 Using ABMs to integrate elements from different disciplines for ambitious climate policy

in an algorithmic form, ABMs are particularly capable of accommodating behavioral realism of diverse actors, describing all kinds of limited rationality as well as social networks underlying the diffusion of information, norms and behaviors (e.g., consumption, voting or lobbying). These features make ABMs particularly useful to study the influence of social and environmental policies on choices by individuals and organizations and, indirectly, on the system as a whole.

The use of ABMs for social-science research and policy advice has proliferated over the last decade (Bianchi & Squazzoni, 2015; Conte & Paolucci, 2014; Dawid et al., 2018), thanks to advances in computing power, access to detailed household- and firm-level data, and availability of a multitude of suitable modeling packages and platforms (Abar et al., 2017; Foramitti, 2021; Gill et al., 2021). ABMs have already seen considerable application to climate change adaptation and mitigation (Brown et al., 2017), socio-technical energy transitions (Hansen et al., 2019), socio-ecological systems (Bourceret et al., 2021), and climate-energy policy (Castro et al., 2020). This includes some fairly complex and data-driven models, like EURACE with its distinction of different regions and sectors of the European economy (Dawid et al., 2019); or the one by Poledna et al. (2020) explicitly modeling around 10 million people and legal entities in Austria, thus allowing for a fine-grained estimation of potential losses due to the COVID-19 lockdown.

In the past, several studies compared agent-based modeling with alternative approaches to design climate change mitigation policies. For example, Rai and Henry (2016) compared it with system dynamics and dynamic discrete choice models for consumer energy choices. They conclude that these other approaches tend to limit themselves to studying perfectly rational agents and abstract away from individual heterogeneity and consumer interaction over social networks. The latter argument is supported by Rahmandad and Sterman (2008) who show that by assuming agents to be homogenous in their attributes, system dynamics models will often misestimate the speed of relevant economic processes—be it diffusion of information, spread of behaviors or adoption of new products—and thus, result in ill-advised policy. Similarly, integrated assessment models, depicting climate stabilization scenarios, have a strictly exogenous preference underpinning, limiting their ability to model lifestyle changes (Creutzig et al., 2022).

Further comparison of ABMs with equilibrium-based models that are still prevailing in the context of applications to climate economics has been provided by Balint et al. (2017). They find that the latter type of models is limited to address technological innovation and modern financial markets since markets there are represented in an over-simplified way (e.g., negligible transaction costs, perfect information), and innovation is not influenced by the dynamics in the model. In contrast, ABMs can model information asymmetries between financially constrained actors (Fagiolo & Roventini, 2017) and study the role of learning and imitation for technological progress (Cowan, 2005; Savin, 2021). Furthermore, they argue that ABMs are better suited to study coalition formation and climate negotiation, since one can represent countries as adaptive players bargaining about their emission reduction and adjusting their strategies in response to other players. This stands in large contrast to static one-shot games commonly prevailing in computable general equilibrium models (Paroussos et al., 2019; Shaw & Fu, 2020) and thus preventing to study how a coalition of actors emerges in the first place.

To understand the long-term effects of climate policies, it is important to account for all relevant aspects of structural change in the economy, including sectoral composition, industrial organization, technical change, employment, demand, and institutions. A literature review by Ciarli and Savona (2019) compared ABMs with a range of model types including, among others, impact assessment and computable general equilibrium models. The authors conclude that the alternatives to ABMs are aggregate in nature (e.g., in terms of technical change components), consider industry relations through input–output coefficients as fixed and avoid addressing some of the above-mentioned aspects.

3 | INTEGRATING ELEMENTS FROM DIFFERENT DISCIPLINES THROUGH AGENT-BASED MODELING

To illustrate how the integration of elements from specific disciplines through ABM can contribute to better analysis of climate policy, we present here three examples that combine dominant disciplines in the literature on climate policy modeling. The first pair of disciplines, behavioral and management sciences, study how agents make decisions. The second set of disciplines, sociology and psychology, examine the nature and consequences of interactions among agents. Finally, the third pair of disciplines, political and economic sciences, address different aspects of policy making from design through implementation to impacts.

3.1 | Combining elements from behavioral and management sciences

Economic agents in standard climate-policy models, be it firms or households, tend to be represented as perfectly informed and utility or profit maximisers. However, it has long been acknowledged that in reality agents rather "satisfice" their goals, such as through the use of individual habits or organizational routines. Moreover, the latter can be updated if showing unsatisfactory performance or as new information and technologies appear (Simon, 1955; Winter, 1971). Failing to account for such behavioral realism can lead to erroneous policy advice (Kirman, 1992).

While representing realistic behavior in models has been acknowledged as relevant to economic (Battiston et al., 2016) and financial policy (Farmer & Foley, 2009) analysis, the literature on climate policy is very much dominated by modeling rational agents (Wei et al., 2015). In particular, the literature to understand the role of bounded rationality for carbon rebound or how norms, lifestyles and culture change in response to climate policy intervention is still incomplete and scattered. ABMs are well capable of formalizing habits and routines, using insights from behavioral economics and management science, respectively (Konc & Savin, 2019; Midgley et al., 1997; Steinbacher et al., 2021). Hence, they can contribute to better policy advice by assessing robustness of findings against a wide range of behavioral assumptions and, thus, help to make policy choices to effectively reduce emissions. ABMs allow to model heterogeneous and dynamic expectations of investors about the future, which combined with learning curve of renewable-energy technologies shows how to stimulate investments in these technologies and increase the effectiveness of carbon pricing (Kraan et al., 2018). In addition, ABM studies can explicitly model bidding behavior of firms on the permit auction and identify the conditions under which emission prices exhibit stability or bubble phenomena (Foramitti et al., 2021a).

3.2 | Combining elements from sociology and psychology

Traditional climate-policy models tend to represent individuals as having stable preferences and being isolated from their social environment (Roos & Hoffart, 2021). Yet, in reality, people make decisions under the influence of their peers (Bamberg et al., 2007; Engelmann & Hein, 2013), which may cause their preferences to change. Studying this requires accounting for relevant elements from sociology and psychology, which ABMs are well equipped for (Jager, 2017). Indeed, ABM studies indicate that social interactions trigger changes in agents' awareness and knowledge, leading to a wider diffusion of low-carbon products and energy-saving habits (Niamir, Kiesewetter, et al., 2020b).

A recent analysis using an ABM by Konc et al. (2021) explores the role of social reinforcement of consumption behavior in response to a carbon tax. It shows that next to the direct price effect reducing emissions there is also an indirect peer effect through social networks which amplifies the emission-reduction effect of the tax. This so-called "social multiplier" of environmental policy allows to reach the same emission reduction target with a considerably lower tax rate than in the case of absence of social influence among consumers. Since less stringent policies tend to garner more public support (Beiser-McGrath & Bernauer, 2019; Lachapelle et al., 2012), this finding contributes also to improved feasibility of climate policy. In a similar vein, Rai and Robinson (2015) show that peer effects allow for lower subsidies for adopting residential solar photovoltaic to achieve emission targets. All these studies underpin that accounting for social interactions is essential to identify the appropriate stringency level and ultimate effectiveness of climate policies, which in turn is likely to affect their public support. Quantifying these effects without realistic representation of interaction over social networks would not have been possible, and this is where the integrative role of ABMs over alternative methods makes a difference.

Another important insight from psychology suggests that people's quality of life, which is both a driver of human behavior and a basis for policy evaluation, depends on the satisfaction of multiple human needs (Costanza et al., 2007; Foramitti, 2023; Sirgy, 2021). Following this theory and using an ABM to study diffusion of electric vehicles, Kangur et al. (2017) find that effective policy requires a combination of monetary, information, and infrastructural measures.

3.3 | Combining elements from political and economic sciences

Agents within an ABM can easily be modeled as heterogeneous in income, political views, spatial location or other features. This not only facilitates the analysis of distributional impacts, but also can help to improve our understanding of the factors underlying support of, or resistance to, climate mitigation policies. Indeed, the two are closely connected since people will resist the implementation of a policy that lacks attention for fair and equitable outcomes (Maestre-

Andrés et al., 2021). Witness the Yellow Vest movement in France, which drew attention to the diversity between people living in cities and the countryside, in turn suggesting spatially differentiated climate policies (Creutzig et al., 2020).

To model policy acceptance, it is necessary to draw lessons from political science on how political-party coalitions and social movements emerge and develop, how voters' knowledge and lifestyle affect their decisions, or how political attitudes change over time. This implies stepping away from a linear model of policy making and considering it as a complex process involving repeated interactions between objective information, subjective opinions, social interactions, political processes and stakeholder lobbying (Grundmann & Rödder, 2019).

While it is clear that policy design depends on social support, few studies have actually analyzed their co-evolution, and all of these employ ABMs. For example, a study by Gerst et al. (2013) develops an ABM to describe countries negotiating international climate policy targets that reflect the preferences of their constituent firms and households. A study by Isley et al. (2015) explores how political lobbying by industry can affect the stringency of climate policies and what this means for the speed of a transition to a low-carbon economy. Similarly, Niamir, Ivanova, and Filatova (2020a) find that climate policy within the EU stimulates regional inequality, in turn compromising the cohesion of the union and undermining its political support. A recent study by Konc et al. (2022) develops a model of the co-dynamics of climate policy stringency and public support. It compares carbon tax and performance standards with different stringency trajectories over time, also accounting for distinct options of tax revenue recycling. It was calibrated by survey data from Spain to inform how information on policy effectiveness, changes in personal well-being and inequality affect policy support. The model allows voters to exchange opinions on policy support within a social network demonstrating that wealthier and socially more influential agents can under certain circumstances change the majority opinion. The study finds that by redistributing carbon tax revenue to low-income households and gradually increasing the tax rate, one can ensure—under realistic parameter value ranges—a majority of voters supports the policy at any point in time. Finally, ABMs routinely integrate behavioral, social and political processes of opinion formation to better examine how individual gains and losses ultimately translate into overall political support of effective policies (Kapeller & Jäger, 2020; Kollman & Page, 2006).

It should be noted that the three cases presented are important though merely illustrative. This does not imply that other disciplines cannot contribute to further advancing our knowledge about climate policies. Table 1 presents more examples on how ABMs can overcome the traditional barriers between different disciplines that prevent systematic communication and synthesis of elements to shed more light on important policy questions.

4 | LIMITATIONS AND DIRECTIONS FOR FURTHER RESEARCH

In each model type trade-offs and limiting choices are inevitable—and the same holds true for agent-based modeling. One important limitation given the complexity of ABMs and their capacity to include multiple types of highly diverse agents is how to ensure that they reasonably well represent real world phenomena.

Castro et al. (2020) earlier have shown that ABMs typically draw data for their empirical calibration from statistical offices, literature and surveys. Still, only some ABM studies contain details on their calibration and validation, and more must be done in this direction. A study by Mueller and de Haan (2009), for example, uses data from Switzerland about consumer income and preferences as well as on prices and sales of cars combined with fiscal measures to reduce CO_2 emissions from new passenger cars, and make their ABM reproduce aggregate market dynamics as well as market share evolution of distinct car types. Rai and Robinson (2015) use detailed demographic, spatial and social network data for almost 2,00,000 households in Austin, Texas and demonstrates high accuracy in predicting technology adoption. In a study of the electricity market of Germany, Herrmann and Savin (2017) combine data on the history of the energy policy mix with that on household income and preferences. This allows them to reproduce the diffusion of renewable energy technology, before proposing an alternative policy mix that could have reached a higher diffusion rate.

If little information on the phenomenon of interest is available to calibrate ABMs, extensive sensitivity analysis ensuring robustness of results is necessary (Rahmandad & Sterman, 2008). While there are modern packages for this purpose (Saltelli, 2002; Sobol, 2001), doing this is still very demanding both computationally and cognitively (Foramitti et al., 2021b). Alternatively, what one can do is to combine within one model elements from agent-based modeling and equilibrium models, as illustrated by recent studies of Niamir, Ivanova, and Filatova (2020a) and Konc et al. (2022). Such a linked-model approach can limit model complexity and simplify comparison with the existing literature. Thus, integration with other model types is welcomed as well, but we think that ABMs can play a unique and critical role in integrating disciplines for the purpose of climate change mitigation.

TABLE 1 Illustrating the added value insights for climate policy advice from integrating disciplinary elements using ABMs

Disciplines combined	Features feasible in ABMs	Illustrative policy question
Economics & psychology	Market interaction, bounded rationality, uncertainty, and learning	How robust are traditional policy insights under bounded rationality?
Economics, psychology & sociology	Market interaction, social networks, human needs, quality of life, endogenous preferences, role of information	What policy combinations lead to climate mitigation while enhancing human quality of life at the same time?
Economics & political science	Coalition formation, firm heterogeneity, distributional effects	How does lobbying by companies influence policy outcomes?
Sociology & psychology	Bounded rationality, social networks, heterogeneous preferences	Which network topology enhances propagation of low-carbon behavior?
Political science & psychology	Collective action, voting, opinion formation, and social learning	How does opinion formation contribute to climate-policy acceptance?
Economics & sociology	Household heterogeneity, consumer practices, social interaction, learning	How does social interaction influence diffusion of green consumer practices?
Economics, psychology, sociology & political science	Market interaction, social networks, bounded rationality, and voting behavior	How to adapt policy over time to meet policy goals and assure sufficient support?
Economics, geography, and psychology	Spatial modeling, life satisfaction, physical environment, human needs	Which urban policy mix minimizes emissions under equal or increasing life satisfaction?
Sociology, psychology and media sciences	Information filtering, echo chambers, bounded rationality, opinion polarization	How to regulate green advertising in electronic social networks?
Agriculture, geography, economics	Life-cycle assessment, farm management, cropping activity, risk aversion, subsidies	How to design policy mixes (regulation and subsidies) for farmers to reduce emissions while guaranteeing viability?

Just like any model, ABMs require simplifications of reality to limit model complexity. To avoid that important details are lost, one may discuss ABM assumptions and outputs with policy stakeholders or undertake pilot study and monitor policy outcomes. This is in line with advice from Klenk and Meehan (2015) that policymaking in the context of complexity and uncertainty is best experimental and adaptive to responses from affected stakeholders. Using ABM for stepwise policy implementation while taking feedback from stakeholders into account would be the next step in in bringing policy science closer to the needs of policy makers.

5 | CONCLUSIONS

The importance of integrating elements from different disciplines as illustrated in this Perspective underpins the potential of ABMs to facilitate the formulation of effective and equitable climate policies. In turn, these policies assure appropriate stringency levels to meet climate targets and sufficient social and political support. Using ABMs for climate-policy analysis can further limit the number of policy scenarios, in turn allowing to focus on those that score well on all performance criteria. In addition, ABMs offer a platform to coherently compare the effects of different policy instruments that are currently predominantly analyzed in isolation by individual disciplines, such as market-based instruments in economics or information policies in psychology. Some existing ABMs already go in this direction, but a more systematic approach using ABMs is warranted. It could ultimately lead to stronger support for ambitious climate policy among scientists, the general public, and policy makers.

AUTHOR CONTRIBUTIONS

Ivan Savin: Conceptualization (lead); writing – original draft (lead). **Felix Creutzig:** Conceptualization (equal); writing – original draft (equal). **Tatiana Filatova:** Conceptualization (equal); writing – original draft (equal). **Joël Foramitti:** Conceptualization (equal); writing – original draft (equal). **Théo Konc:** Conceptualization (equal); writing

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DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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