Article Title: A Review of Agent-based Modelling of Climate-Energy Policy

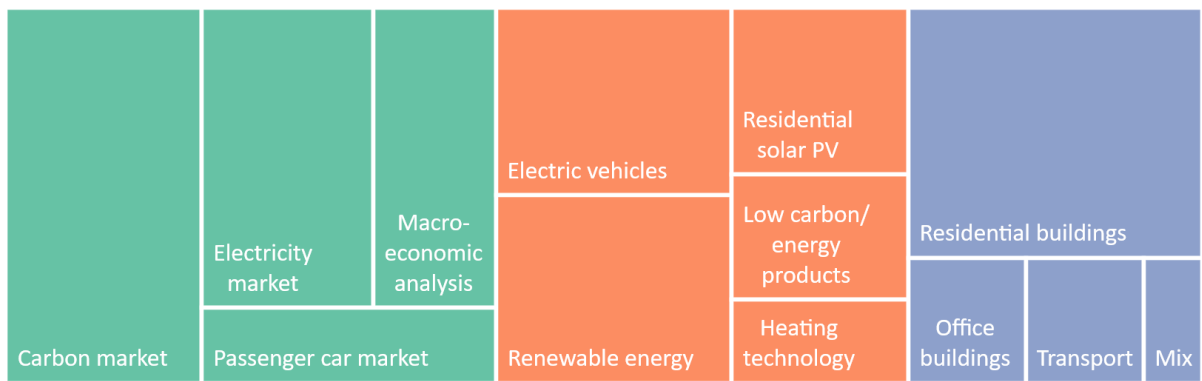**Article Type:** Advanced review

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Abstract: Agent-based models (ABMs) have recently seen much application to the field of climate mitigation policies. They offer a more realistic description of micro behaviour than traditional climate policy models by allowing for agent heterogeneity, bounded rationality and non-market interactions over social networks. This enables the analysis of a broader spectrum of policies. Here, we review 61 ABM studies addressing climate-energy policy aimed at emissions reduction, product and technology diffusion, and energy conservation. This covers a broad set of instruments of climate policy, ranging from carbon taxation and emissions trading through adoption subsidies to information provision tools such as smart meters and eco-labels. Our treatment pays specific attention to behavioural assumptions and the structure of social networks. We offer suggestions for future research with ABMs to answer neglected policy questions.

Graphical/Visual Abstract and Caption:

1. Introduction

The design of effective climate policies requires a good understanding of how agents behave and interact with others. Traditional studies of such policies use models that rely on simplifying assumptions of representative agents that are rational and self-interested, while lacking social interactions (Babatunde et al., 2017). Insights from behavioural economics, social psychology and other disciplines challenge such assumptions (e.g., Rabin, 1998; Thaler, 2016), suggesting the need for a richer treatment of human behaviour in climate policy studies. Agent-based models[1] (ABMs) represent an individual-based microsimulation approach that can integrate relevant aspects of human behaviour and diversity, and thus provide a much-wanted link between systemic policy analysis and behavioural economics. They are suited to describe agent heterogeneity, bounded rationality, other-regarding preferences, market and non-market behaviours, and social networks. This approach allows for testing a wide range of climate and energy policies under more realistic settings, including less studied policies such as particular types of information provision (e.g., smart meters) or combinations of pricing and information instruments.

This review presents an overview of 61 ABM studies in this emerging area of research, taking stock of model design, policy dimensions and empirical underpinnings. Its purpose is twofold. First, we aim to clarify core features of ABMs of climate-energy policy, such as application types, empirical basis, market designs, agent behaviours, and social network structures. This is relevant as it shows the combinations of choices already studied, allowing model developers to identify gaps and opportunities for further work. Second, we identify policy dimensions, including problems addressed, policy objectives, instruments, scenarios and insights. From this, we derive a set of topics for future research.

Several other studies have reviewed the application of ABMs to climate and energy issues. These focus on climate adaptation or land-use issues (Arneth et al., 2014; Berger and Troost, 2014; Brown et al., 2017; Groeneveld, 2017), specific aspects of energy demand, energy efficiency or travel choice (e.g., Rai and Henry, 2016; Moglia et al., 2017; Hansen et al., 2019; Hesselink and Chappin, 2019), or a broader environmental (policy) context (Heckbert et al., 2010). Our review complements this existing literature in several respects. First, we focus on climate mitigation through emissions reduction by firms or households, such as through abatement, diffusion of low-carbon products and technologies, and energy-efficiency improvements. This involves attention for selected energy studies that explicitly deal with emissions and climate-energy policy. Second, unlike the reviews mentioned above we comprehensively classify modelling choices made in the reviewed studies, such as types of agents or markets described and data sources used. Third, we pay detailed attention to behavioural assumptions in ABMs of climate policy, assessing agent heterogeneity, types of bounded rationality, social interactions and associated network configurations. We hope that these details will help researchers to learn about best practices and potential pitfalls. Finally, unlike most other reviews, we cover not only models with a partial scope – e.g. describing a single market or diffusion of one product – but also with a general – economy-wide or macroeconomic – coverage. One may regard the latter as providing more robust insights given that they are able to look beyond partial effects of policies. In Section 3 we will provide more information on the difference between the current and previous reviews.

The paper proceeds as follows. Section 2 provides an overview of general aspects and applications of ABMs stressing their strengths compared to alternative modelling approaches. Section 3 discusses the selection of studies and method of reviewing employed. Sections 4 and 5 address the first aim of this study, with Section 4 reporting general features of the reviewed models, including motivations, markets and empirical foundation, and Section 5 reviewing the choices made in ABMs regarding agents, in terms of heterogeneity, types of bounded rationality, and social interactions and networks. Section 6 addresses the second aim of the study by reviewing policy goals and instruments and illustrating how policy insights relate to model features. Section 7 identifies challenges that ABMs face and their potential uses for further study of climate policies. Section 8 concludes.

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[1] Alternative terms are "agent-based complex systems" (Grimm et al., 2005), "individual based models" (Grimm and Railsback, 2005), "agent-based computational economics" (Tesfatsion, 2006), "complex adaptive systems" (Miller and Page, 2007) and "multi-agent systems" (Heckbert et al., 2010).

2. Agent-based modelling

Agent-based modelling has received increasing attention in a variety of disciplines over the past decade. It simulates the dynamics of complex systems based on describing the continuous interaction of agents who are heterogeneous in terms of information and decision rules. The origins of ABM can be traced back to mathematical game theory (von Neumann and Morgenstern, 1944). Nobel laureate Schelling (1969, 1971) applied this theory to issues of conflict and cooperation, resulting in an early application of agent-based modelling to describe the process underlying racial segregation of residences in cities. Another foundation is the cellular automata model,[2] with its famous early application to "The Game of Life" by John Conway (Gardner, 1970). Cellular automata have subsequently been applied in physics, biology, landscape ecology and environmental science (Wolfram, 1986). The method started to become popular in the social sciences during the 1990s thanks to advances in computing technology.

ABMs signify a move away from assumptions of the representative consumer and firm that characterize traditional policy models. Empirical and experimental behavioural research demonstrates considerable heterogeneity of both types of agents in reality (Heckman, 2001). ABMs respond to this by describing one or multiple populations of agents with internal diversity in terms of bounded rationality and other-regarding preferences (De Grauwe, 2011). In addition, many models include social interactions in terms of information sharing or behavioural spillovers (Powell, 1998; Savin and Egbetokun, 2016). This allows addressing important behavioural phenomena, such as conformism, status seeking and imitation. Thanks to their bottom-up approach (Delli Gatti et al., 2011), ABMs translate local interactions at the micro level to aggregate or macro patterns allowing for a more comprehensive policy assessment (Dawid and Neugart, 2011).

Many ABMs employ heuristics rules to describe behaviour. Agents can switch between these or adapt them in response to their performance relative to others (Anufriev and Hommes, 2012). This involves agents comparing the rules they have available with those used by peers (Ichinose et al., 2013; d'Andria and Savin, 2018). Examples of heuristics include selection of R&D partners based on cognitive distance (Cowan and Jonard, 2004), forming expectations about future demand or prices (Lamperti, 2018), and design of mark-up pricing (Dawid et al., 2012).

Unlike traditional models, ABMs can accurately describe direct (sometimes called "local") interactions between agents in a population of people or organizations. Similar to the real world, agents have different propensities to interact, depending on their location in a relevant spatial or social network (Breschi and Lissoni, 2009). One can tune the network to empirical data, such as spatial locations of households, locations of power plants in an electricity grid, an existing system of interbank loans, or patent networks (Korzinov and Savin, 2018). This allows one to estimate structure – comprising degree distribution, clustering and assortativity – and density of the network. ABMs can describe distinct network topologies encountered in reality, for example, small world or scale free networks (Mueller et al., 2017; Konc and Savin, 2019).

A further advantage of ABMs is that they allow combining market and non-market relations in a single framework. The latter relations involve agent interactions over social networks. As a result, ABMs allow studying combinations of policy instruments that employ market and non-market mechanisms, such as taxes and information provision. This allows one to address how market choices and social interactions between agents influence each other and, linked to this, how associated policies interact, i.e. whether they are negatively or positively synergistic. Policies using extrinsic incentives (e.g. taxes) may be complementary to information policies appealing to intrinsic motives, or they may undercut them (e.g. Pellerano et al., 2017). ABMs offer a tool for studying this.

ABMs have been advocated as a particularly suitable modelling tool for studying climate and energy policies (Farmer et al., 2015). In a survey of the economics of climate change from a complexity perspective, Balint et al. (2017) motivate the relevance of agent-based models by arguing that agent

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[2] Stanislaw Ulam and John von Neumann developed this technique in the 1940s. It describes a regular grid of cells, each with a value or state determined by the values of cells in its direct neighborhood, and possibly also by its current value. This gives rise to a dynamic pattern of cell states that either continues changing or ends in a stationary state or cyclic pattern.

heterogeneity and learning affect the speed of a transition to a low-carbon economy. Hoekstra et al. (2017) provide practical advice for ABM construction, but neglect somewhat behavioural aspects. Recently, Lamperti et al. (2019) discussed how to use agent-based modelling for integrated assessment, stressing the superiority of ABMs in addressing complex problems such as climate change.

Of course, ABMs also have certain disadvantages. Multiple agents, network interactions and bounded rationality tend to translate into considerable model complexity and many parameters. This sometimes complicates the interpretation of model outcomes while it also creates challenges for parameterization, calibration and validation (Winker and Gilli, 2001; Janssen and Ostrom, 2006; see also Section 4.3). To deal with this, some parameter values can be drawn from realistic distributions while others can be calibrated on model output, guided by so-called 'stylized facts' from empirical research, such as skewed firm-size distributions (Carroll and Hannan, 2000), clustering of innovative activity in time (Frenken, 2006), or observed historical paths of a particular industry or market under investigation (Garavaglia, 2010).

3. Search and selection of studies

Our review focuses on ABMs studying climate-energy policies that have a close relationship with the reduction of greenhouse gas emissions. This includes three broad categories of studies, namely offering an analysis of policies that directly trigger emissions reduction, that stimulate the diffusion of low-carbon/energy products and technologies, and that encourage energy conservation. The latter two contribute more indirectly to emissions reduction. These three themes, and associated sub-themes, are visualized in Table 1. Hence, we offer a selective rather than a systematic literature review. It excludes adaptation to climate change (see Aerts et al., 2019), as well as climate mitigation in a broader sense, i.e. compensating anthropogenic emissions such as through forestation. This was already covered in previous reviews of ABMs applied to land-based sectors, such as agriculture, forestry and nature conservation (Arneth et al., 2014; Berger and Troost, 2014; Brown et al., 2017; Groeneveld, 2017).

Table 1. Types of applications in the reviewed studies

Theme (# studies)	Sub-theme	Studies
Emissions reduction (25)	Carbon market (10)	Matsumoto, 2008; Chappin et al., 2009; Richstein et al., 2014; Richstein, 2015; Tang et al., 2015; Isley et al., 2015; Lee and Han, 2016; Zhu et al., 2016; Tang et al., 2017; Zhu et al., 2018
	Electricity market (7)	Veit et al., 2009; Chen et al., 2013; Beckenbach et al., 2017; Li, 2017; Li and Strachan, 2017; Kraan et al., 2018; Wu et al., 2018
	Macroeconomic analysis (5)	Gerst et al., 2013; Monasterolo and Raberto, 2016; Lamperti et al., 2018; Monasterolo and Raberto, 2018; Rengs et al., 2020
	Passenger car market (3)	Mueller and de Haan, 2009/de Haan et al. (2009)*;van der Vooren and Brouillat, 2015; Hofer et al., 2018
Product/technology diffusion (21)	Electric vehicles (6)	Köhler et al., 2009; Eppstein et al., 2011; Natarajan et al., 2011; McCoy and Lyons, 2014; Silvia and Krause, 2016; Kangur et al., 2017
	Renewable energy (6)	Nannen and van den Bergh, 2010; Ernst and Briegel, 2017; Herrmann and Savin, 2017; Safarzynska and van den Bergh, 2017a; Chen et al., 2018; Ponta et al., 2018
	Residential solar PV (4)	Palmer et al., 2015; Rai and Robinson, 2015; Wang et al., 2018a; Irsyad et al., 2019
	Low carbon/energy products (3)	Bleda and Valente, 2009; Desmarchelier et al., 2013; D'Orazio and Valente, 2019
	Heating technology (2)	Sopha et al., 2011; Sopha et al., 2013

Energy conservation (15)	Residential buildings (10)	Damiani and Sissa, 2013; Lee et al., 2014; Hicks and Theis, 2014; Hicks et al., 2015; Kowalska-Pyzalska, 2016; Jensen and Chappin, 2017; Walzberg et al., 2017; Moglia et al., 2018; Niamir et al., 2018; Wang et al., 2018b
	Office buildings (2)	Azar and Menassa, 2011; Zhang et al., 2011
	Transport (2)	Schröder and Wolf, 2017; Safarzynska and van den Bergh, 2018
	Multiple domains (1)	Allen et al., 2018

Note: Mueller and de Haan (2009) and de Haan et al. (2009) are one study split into two publications (namely, subsequent articles in the same journal issue). We therefore treat (and count) them as one study in the table and the rest of the paper.

Focusing on the themes indicated above, our approach involved a search in Google Scholar and Scopus for relevant keywords, including combinations of three types of terms: (i) carbon, climate, emission, energy, environment, and rebound; (ii) policy, tax, tax reform, emission trading, permit market, and information provision; and (iii) agent based model(ling), ABM, micro-simulation, simulation model, and evolutionary model. This generated a very long list of publications in Google Scholar. We scanned many Google Scholar pages for titles to see if the respective studies addressed the themes, offered a concrete and innovative model, and were relevant for climate policy – until the success rate dropped to zero, i.e. the next and various subsequent Google Scholar pages did not return any relevant ABM studies of climate policy. Of the thus obtained set, we read the abstract, which further reduced the number of relevant studies significantly. Next, we went through the reference lists of the remaining publications, which in turn increased the set of relevant studies. Finally, we excluded publications that offered little information about the actual model, or were based on models already described in earlier publications in the set of studies. This search procedure started in September 2018 and was finished in January 2019. The resulting selection covers a total of 61 studies.

In terms of applications, the reviewed studies cover three thematic categories and associated sub-themes. Table 1 provides an overview, while also giving frequencies of applications (note that colours for themes are used consistently in all figures and tables). The largest group of 25 studies explicitly models reduction of greenhouse gas emissions. Specific issues here relate to electricity, passenger-car and carbon markets, while broader macroeconomic models cover multiple markets simultaneously. The second largest category concerns product/technology diffusion, with 21 out of 61 papers. These cover residential solar photovoltaics, heating technology, general renewable energy technologies, and low-carbon/energy products and electric vehicles. To illustrate, Bleda and Valente (2009) analyse the influence of information provision through eco-labelling of low-carbon goods on consumer choices, while Desmarchelier et al. (2013) compare the efficacy of eco-labelling with that of an environmental tax. The third largest category, with 15 out of 61 papers, addresses energy conservation and related policies. These studies usually study energy use in either residential or office buildings. In addition, Schröder and Wolf (2017) consider the role of car-sharing for transportation, while Allen et al. (2018) look at the role of sustainable lifestyle diffusion focused on the consumption of energy, transport and food. Needless to say, perhaps, the reviewed studies cover policy analyses involving single instruments as well as policy packages – i.e. mixes or combinations of instruments.

4. Motivations and basic features of the reviewed studies
4.1 Reasons for using ABM
In the reviewed literature, the choice of agent-based models is motivated in several ways. A frequent reason, in all three thematic categories, is the possibility to introduce multiple agents of one type, such as consumers or firms in a particular sector, as this allows for addressing heterogeneity and social interactions. This argument relates to a more general motivation, namely that ABMs follow a bottom-up structure in describing economies and their dynamics (Ponta et al., 2018; Tang et al., 2015; Lamperti et al.; Safarzynska and van den Bergh, 2018). Another common reason is the possibility to describe bounded rationality, such as through non-optimal decision rules or adaptive learning. This argument

pertains especially to studies on product/technology diffusion, where agents are not necessarily perfectly informed about available options or may have reasons other than price to adopt a certain technology (Bleda and Valente 2009, Safarzynska and van den Bergh 2017a, Herrmann and Savin, 2017).

In addition, many studies stress the relevance of considering interactions among agents in social networks to describe realistically the diffusion of knowledge, behaviours or products. In doing so, agents learn about the social environment they are acting in and adopt relevant behaviours (Nannen and van den Bergh, 2010). Agent interactions are driven by heterogeneity of agents in terms of income, preferences, behavioural rules or social network position. Using ABMs to account for social interactions among heterogeneous agents is suggested to serve as a kind of robustness test for results obtained with homogeneous, isolated agents (Gerst et al., 2013). This relates to the role of peer influence, which appears as relevant in certain thematic sub-categories, namely on passenger car market, diffusion of low-carbon/energy products and technologies, and residential buildings. Finally, studies focusing on the evolution of certain markets or entire economies note the suitability of ABMs to study out-of-equilibrium or transitionary processes (Ponta et al., 2018). This contributes to testing the effectiveness of transition policies (van den Bergh, 2013) or system responses to policy shocks (Lamperti et al., 2018). This reason is more common for studies on emission reduction and product/technology diffusion.

4.2 Number and types of markets

The number of modelled markets in the reviewed studies – i.e. with prices, demand or supply explicitly described - ranges from zero to 100. Some studies do not describe a market explicitly, i.e. with demand, supply and prices, even though implicitly there is one. Examples include Palmer et al. (2015), who model the decision process for solar PV adoption, and Ernst and Briegel (2017), who consider the implicit market for green electricity focusing on factors influencing psychological decision-making. In a study by Nannen and van den Bergh (2010), each agent represents a government controlling a separate economy, meaning they implicitly describe 200 (aggregate) markets. Another outlier is a study by Wu et al. (2018) who implicitly model 100 local energy markets. The mean number of 6.6 markets and a median of 1 indicate strong dispersion, with a high number of studies analysing only a few markets simultaneously (if we exclude the outliers with many implicit markets the mean value drops to 2.0). The studies describe a great diversity of markets, including for physical capital, generic consumption, energy-generating equipment, transportation, electricity, financial services, labour, raw materials and carbon permits. Modelled most frequently are electricity markets or markets for a generic final consumption good, which appear in 16 and 15 of the studies, respectively. Carbon permit markets are modelled in around 11 studies, followed by capital markets in eight and financial markets and energy-related consumption in six studies. Out of the 11 studies of specific consumer goods, energy equipment – such as solar panels or heat pumps – are modelled six times and private transport five times.

The majority of the papers in our sample considers fewer than three markets while only twelve studies analyse three or more markets. Table 2 gives an overview of the frequency with which different combinations of markets appear. Some markets are more likely to be analysed in isolation compared to others. This applies in particular to specific consumption goods. Associated studies are often focused on product/technology diffusion and household adoption behaviour (e.g. Sopha et al., 2011; Rai and Robinson, 2015; Herrmann and Savin, 2017; Wang et al., 2018a). Studies tend to use a generic consumption good in combination with multiple markets. Only six out of 15 models analyse such a good by considering a single market. Electricity markets appear in all combinations, except with other energy markets. Carbon permit markets are analysed more in isolation. Their combinations are limited to generic consumption, electricity and raw material markets in the underlying sample. Incidentally, labour markets are never analysed together with carbon markets.

Regarding themes, among studies on emissions reduction almost all market types are found, while markets for carbon permits, electricity, generic consumption goods and capital goods dominate – appearing in 10, 8, 8 and 7 studies, respectively. Studies on product/technology diffusion tend to focus on markets for generic consumption goods, electricity and energy-related consumption goods – appearing in 7, 6 and 5 studies, respectively. Studies on energy conservation model specific consumption markets (2) and energy/electricity markets (4), while most do not model any market (9). Finally studies

on the first theme, and to a lesser extent on the second theme, also include various models that describe interactions among multiple markets.

Table 2. Frequency of combination of distinct markets in the reviewed studies

	CAP	CAR	GCG	SCE	SCT	EL	EN	FIN	LAB	OTH	RM
Capital (**CAP**)	8	0	6	0	0	2	2	4	3	2	3
Carbon (**CAR**)		11	3	0	0	4	0	0	0	0	1
Generic consumption (**GCG**)			15	0	0	3	1	6	4	2	4
Specific consumption, energy (**SCE**)				6	0	2	0	0	0	0	0
Specific consumption, transport (**SCT**)					5	1	0	0	0	0	0
Electricity (**EL**)						16	0	3	2	1	3
Other energy (**EN**)							5	0	0	1	0
Financial services (**FIN**)								6	4	1	4
Labour (**LAB**)									4	1	4
Other (**OTH**)										3	1
Raw materials (**RM**)											5

Notes: Darker colour of a cell indicates a higher number of studies. Numbers represent the frequency with which individual markets (diagonal) or combinations of markets (other cells) appear. Numbers per row or column do not add up to total studies reviewed because those with multiple markets appear in multiple cells.

4.3 Empirical basis and time horizon

Parametrization, calibration and validation (PCV) are three procedures to assure realistic and reliable ABMs. Parametrization means taking parameter values from an external source, such as academic or grey literature, a survey, publicly available or commercial data, and (expert) interviews. Calibration denotes tuning of certain (remaining) parameters to assure that model output matches well with relevant empirical data. Depending on a model's complexity and the number of free parameters, calibration may be a long, iterative process (Winker et al., 2007). Validation means assessing whether the model is a reasonably accurate representation of the real world by reproducing empirical regularities (stylized facts) or replicating historical processes. As the three steps are not sharply separated, distinguishing them in the reviewed studies is sometimes difficult.

Of the sources used for PCV in the 61 reviewed studies, we established that 54% used statistical data, 48% parameter values from the literature, 34% data from surveys, and 2% data from expert interviews. This is summarized in the top left graph of Figure 1. Note that the percentages add up to more than 100% as certain studies used multiple sources. To see how often the studies combined them, we counted the frequency of observing single or multiple sources (bottom left graph in Figure 1): 43% used one type of data source only, 38% a combination of two distinct types of sources (typically literature and statistical data) and 6% a combination of survey, literature and statistical data. In addition, 13% of the studies did not report any source information suggesting they were theoretical in nature. None of the studies combined all four types of data sources.
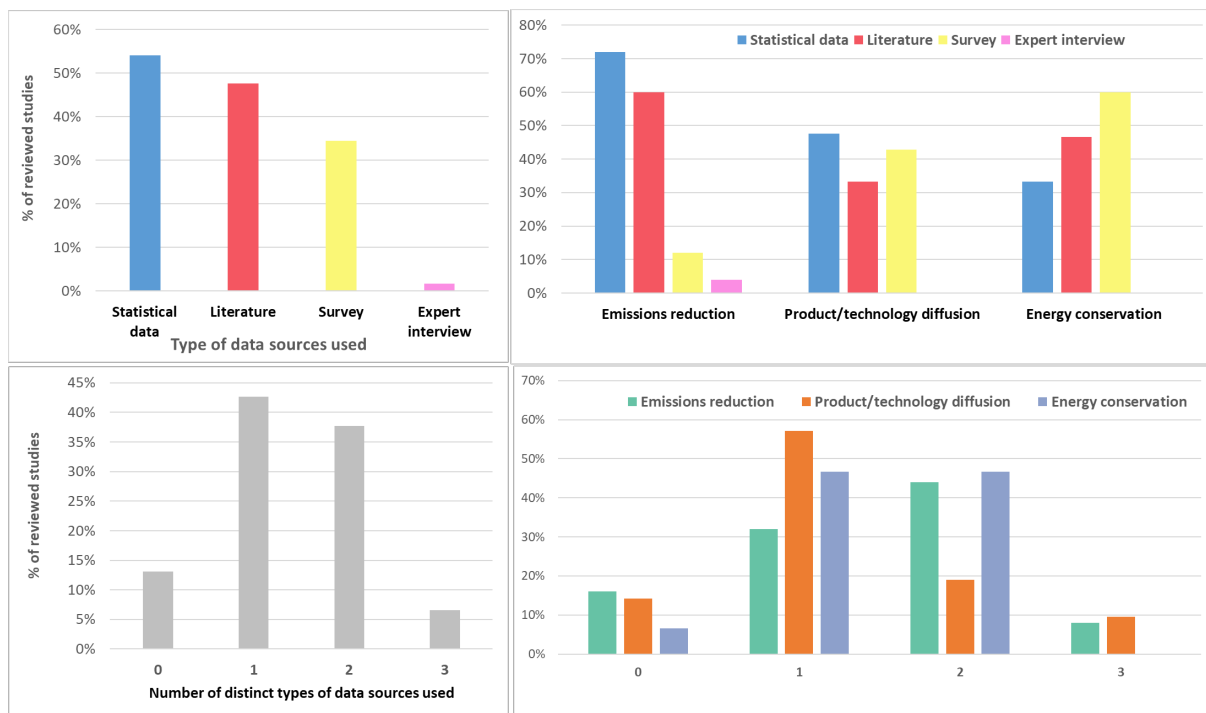
Figure 1. Distribution of data sources for PCV among the reviewed studies

References to earlier studies in the literature are the most common means of identifying stylized facts to be reproduced by models (e.g., Lamperti et al., 2018; or D'Orazio and Valente, 2019) or to select parameter values, such as learning rates of energy generation technologies (Gerst et al., 2013; Herrmann and Savin, 2017). As can be seen from the top right chart in Figure 1, data from the literature appears as a common source across all three thematic categories. Statistical data sources provide information on indicators such as population (World Bank), investment rates (IMF), public taxation and income (countries' fiscal statistical yearbooks). Commercial databases were used to obtain data about firms, such as prices and stocks of products for certain industries (Mueller and de Haan, 2009), or about consumers, such as car ownership, and driving preferences and behaviour (Kangur et al., 2017). Surveys are frequently used as a method for parametrization, motivated by unique data required that is hard to obtain from general, publicly available sources. To illustrate, Niamir et al. (2018) use a survey to inquire about behavioural norms, energy consumption and the type of appliances installed. Surveys are mostly conducted among households but also include some that are aimed at firms. For instance, Chen et al. (2013) surveyed power plants to obtain information on indicators such as carbon intensity and production costs. What we find is that statistical data as a source to tune ABMs is more common for studies on product/technology diffusion and emissions reduction, while surveys are the preferred data source in studies on energy conservation in our sample. This is arguably because the latter require detailed information about energy consumption that tend to be missing from public statistical databases. Expert interviews are rare for all four categories of studies identified. The only one we encountered (Kraan et al., 2018) belongs to the category on emission reduction. Finally, the lower right panel in Figure 1 shows that studies on emission reduction and energy conservation tend to combine distinct data sources slightly more often than studies on product/technology diffusion.

The level of detail of PCV steps varies considerably. More abstract models avoid it by choosing a set-up motivated by a policy goal: e.g., Wu et al. (2018) choose parameters such that low-carbon energy is less attractive in the electricity market, while Bleda and Valente (2009) do the same for all low-carbon goods. Models that lack a specific application to a market, country or period tend to focus on reproducing stylized facts: be it a power law of firm size, fat-tailed GDP growth rates or persistent volatility differentials across firms (D'Orazio and Valente, 2019; Lamperti et al., 2018). In contrast, case-based studies pay more attention to PCV. For example, a study of the car market in Switzerland by Mueller and de Haan (2009) takes sociodemographic data of consumers from the national statistical

agency and data on prices and supply of cars from commercial data sources. Scenarios with different behavioural assumptions are then compared with observed market shares of different car types. A study by Herrmann and Savin (2017) of the electricity market of Germany during 1990-2010 uses parameter values from the literature for learning rates for photovoltaic and wind energy, uses statistical data to define the income distribution of households, and calibrates other parameters to reproduce empirically observed learning and diffusion curves of renewable energy technology.

Finally, time units and horizon vary between the reviewed studies. Two thirds of the reviewed papers (40 out of 61) provide information about the type and number of time steps in the numerical simulations with the ABM. Some studies use a realistic time frame while others present abstract simulations unrelated to any real time period. The latter are slightly more frequent (33 compared to 28). Both the number and length of simulation periods vary widely across studies. Mueller and de Haan (2009) model only one period while the highest number of periods is 8760 (Walzberg et al., 2017). In some models, steps represent thirty minutes while in others they are equivalent to weeks, months or years. For those studies where period lengths could be identified (43), annual periods are most frequently used (25 out of 43), followed by monthly periods (9 out of 43). Among studies on emissions reduction, annual periods are most common. Diffusion and energy conservation studies often use short periods of a week or less. Macro models with a focus on energy or electricity tend to use monthly or quarterly periods. If realistic time periods are described, then time horizons vary between 1975 and 2100, with a mean length of 35 years and a median of 30. Regarding themes, studies on emissions reduction consistently employed a longer time horizons (median of 40 years), motivated by policies under consideration needing more time to produce a complete effect (think of R&D subsidies). In contrast, studies on energy conservation use shorter time horizons (median of 15 years) consistent with changes in relevant behaviours occurring faster. Studies on product/technology diffusion have a time horizon in-between (median 22 years), due to combing studies that look at policies causing slow changes in technology and infrastructure with studies that assess policies aimed at fairly rapid changes in tastes and lifestyles.

5. Agents and their behaviour in the reviewed studies
5.1 Agents: types, numbers, decisions and heterogeneity
Agents in the models are mostly households and individuals (consumers and/or workers) who make decisions regarding consumption, or firms that produce consumer, capital or energy goods. In particular, 28 models include only consumers, 12 include only firms, while 17 include both. Five models include agents that represent banks (either central or commercial) and seven describe governments, regional authorities or policy makers. In studies that model decisions like energy use, adoption of products, production plans or product/technology diffusion, there is typically only one type of agent, while studies that model policies usually try to explore interdependencies between multiple sectors (households, firms, multiple industrial sectors, or banks) and therefore include different types of agents interacting with each other. Regarding the three themes, 13 of the 25 studies on emissions reduction focus on firm behaviour, notably in the sub-theme of electricity market; three studies include only consumers; five additional studies describe firms interacting with consumers, governments or banks; and four represent macro ABMs that include three or more agent types. Among studies on product/technology diffusion, 13 out of 21 focus on consumers, 4 on consumer-firm interactions, 3 consider also banks, and one focuses on multiple (regional or national) governments. Finally, of the studies on energy conservation 14 out of 15 tend to focus on consumers and one on consumer-firm interactions.

Whenever consumers are modelled, the number of agents on average has an order of magnitude of thousands to tens of thousands. Firms appear in smaller numbers in the models, typically less than 50, and in many instances even ten or less. This is not always clearly justified. Three general reasons for this difference could be: in reality the number of consumers exceeds the number of firms by many factors; consumer heterogeneity in the models tends to have more dimensions, requiring a larger population to arrive at an accurate description; and social diffusion, which depends on population size, is generally more relevant to consumer than firm decisions.

Consumers make decisions about the consumption type and/or level. The most common decision is whether to adopt a technology, such as solar PV, a smart meter, etc. Firms decide about production levels or investment and innovation strategies, such as loans from banks, fuel mix or extending generation capacity. In models that include governments, actions include maximising social welfare (Nannen and van den Bergh, 2010; Isley et al., 2015), reducing carbon emissions (Tang et al., 2015; 2017), or stimulating a reduction in heating (Jensen and Chappin, 2017). Some models assign the government a monitor-and-control role, through imposition of penalties for non-compliance (Tang et al., 2015). Finally, in models describing a central bank and commercial banks (see Gerst et al., 2013; Rengs et al., 2020) actions involve collecting deposits and providing loans to firms.

The main factor of heterogeneity across households is their preference for low-carbon goods and more generally their pro-environmental values (26 studies). This heterogeneity allows to accurately describe the demand side for – initially more expensive – low-carbon options and can help to identify the conditions under which an option diffuses rapidly or completely in the population (e.g. Bleda and Valente, 2009). Preferences are often represented as a single parameter (or variable) but can also encompass multiple factors portraying complex lifestyles (Palmer et al., 2015; Ernst and Briegel, 2017). Households or individuals can also differ in their information they possess about the choice space or product characteristics (Nannen and van den Bergh, 2010; Li and Strachan, 2017; Wang et al., 2018a), their susceptibility to social influence (Eppstein et al., 2011; Sopha et al., 2011; Damiani and Sissa, 2013; Hicks and Theis, 2014; Schröder and Wolf, 2017), income (Palmer et al., 2015; Silvia and Krause, 2016; Schröder and Wolf, 2017, Kangur et al., 2017; Herrmann and Savin, 2017; Lamperti et al., 2018), or risk attitude (Chen et al. 2013; Li and Strachan, 2017).

Using ABMs to represent boundedly rational agents allows for novel forms of heterogeneity. For example, in Bleda and Valente (2009) agents have different propensities to make assessment mistakes. To make their decision, agents rank the products, with some error, on environmental and user quality. When the propensity to make assessment mistakes increases, more products with inferior characteristics will remain on the market. Similarly, other studies model heterogeneity in choosing a behavioural strategy in a given situation (Veit et al., 2009; Sopha et al., 2011; Hicks and Theis, 2014; Tang et al., 2017; Moglia et al., 2018).

Heterogeneity of firms often relates to production technology and how this affects competitiveness in a market (Bleda and Valente, 2009; Gerst et al., 2013; Tang et al., 2015; Richstein et al., 2015; Lee et al., 2016; Wu et al., 2018; Rengs et al., 2020; Lamperti et al., 2018; Isley et al., 2018; Chen et al. 2018). This is reflected by heterogeneous production costs and product features, notably their carbon intensity, across firms. When the demand side is modelled with consumers having heterogeneous preferences for "environmental quality", firms choose their technology mix in order to compete in prices (as is usual) or in carbon intensity (Bleda and Valente, 2009; Desmarchelier et al., 2013). Other types of heterogeneity include distinct expectations about the profitability of investments (Richstein et al., 2015; Kraan et al., 2018; Zhu et al., 2018), different pricing rules due to specific mark-ups or local monopolies (Wu et al., 2018), or even dissimilar R&D investment strategies (Chappin and Dijkema, 2009; Lamperti et al., 2018; Isley et al., 2018; D'Orazio and Valente, 2019). In addition, abatement options and costs may differ between firms (Zhu et al., 2016; Lee et al. 2016; Lamperti et al., 2018; Zhu et al., 2018).

5.2 Types of bounded rationality

There is considerable heterogeneity regarding the way agent behaviour is modelled in ABMs of climate mitigation policy. Different authors suggest distinct ways to classify behaviour and decision-making (e.g., Balke and Gilbert, 2014; Kennedy, 2012; Schlüter et al., 2017). Grimm et al. (2006) proposed a protocol – Overview, Design Concepts and Details (ODD) – for reporting ABM studies, which was extended by Müller et al. (2013) to include ten design concepts related to human decision-making. Here we use the widely accepted classification into rationality and bounded rationality in behavioural economics (Sen, 2017; Kahneman, 2003; Thaler, 2016). It has the advantage of limiting the number of behavioural categories, and facilitating a comparison of ABM studies of climate policy with the dominant literature on climate policy modelling which uses rationality as a starting point (Babatunde et al., 2017). Agents may be considered to deviate from full rationality when one of the two following

conditions are met: (i) they make decisions that do not use an optimizing rule, such as maximization of a profit or a utility function; and (ii) they lack perfect information to reach an optimal decision. If one of these conditions is met, agents exhibit boundedly rational behaviour.

Table 3 summarizes the types of boundedly rational behaviour encountered. It distinguishes between deviations from perfect rationality and imperfect information on the other. While one might argue the that latter is part of the first, it appears so frequently and with specific sub-cases in the reviewed studies reviewed that it would be easily overlooked if we would integrate the two categories. In addition, imperfect information is also addressed by theories and models assuming rational agents, and hence can be seen on the boundary of rational and bounded rationality.

The majority of product/technology diffusion and energy conservation studies focus on deviations from perfect rationality by consumers, while most studies on emissions reduction address boundedly rational behaviour of firms. Given that one of the main reasons for using an ABM is describing behaviours that deviate from behaviour of the rational agent model, it is not surprising that most of the reviewed articles (50 out of 61) satisfy at least one of the above conditions. In 38 studies, agents deviate from perfect rationality (in 22 out of 46 models that include consumers as agents, and in 16 out of 31 models with firms), while in 27 studies, agents use imperfect information (14 out of 46, and 21 out of 31 for models with consumers and firms, respectively). Only eight models of consumers and three of firms assumed full rationality. We observe that in the case of consumers, bounded rationality more often takes the form of deviation from a fully optimizing rule than of imperfect information, while the pattern is reverse for firms. Note that under certain conditions, some of elements presented in the table could be consistent with an optimization framework. For instance, imitation can be rational depending on the information agents have (Apesteguia et al., 2007). However, whenever we mention studies in Table 3 it is because they deviate from standard rational behaviour.

Table 3. Most common types of boundedly rational behaviour by consumers and firms in the reviewed studies

	Consumers (35 unique studies)	Firms (26 unique studies)
Deviations from perfect rationality	**22 studies [3/12/7]** Status Quo/Habit[7–13] Threshold[1–6] Imitation[8–11,13,14] Random elements[15–18] Loss aversion[1,19,20,61] Step-decision[20,21] Habits[61]	**16 studies [11/4/1]** Mark-up pricing[22–30] Random elements[29,31–33] Imitation[21,29,34,35] Threshold[21,37]
Imperfect information	**14 studies [6/6/2]** Limited awareness[7,21–23,31–39,40] Choice Subset[5,19,20,24] Myopia[61]	**21 studies [16/6/0]** Myopia / Imperfect expectations[21,26–28,30,34,35,36,39,41–49] Choice Subset[29,38] Not update information[22]

Notes:
a) Order of behaviours reflect frequency.
b) Coloured numbers in square brackets indicate frequency of application to the three themes (colours consistent with the graphical abstract).
c) Numbers in the table do not add up to the total of reviewed studies as several models include multiple behavioural categories (including both consumers and firms).
d) Study numbers refer to: 1. Li (2017); 2. McCoy and Lyons, 2014; 3. Palmer et al., 2015; 4. Rai and Robinson, 2015; 5. Wang et al., 2018a; 6. Wang et al., 2018b; 7. Ernst et al., 2017. 8. Kangur et al., 2017; 9. Moglia et al., 2018; 10. Sopha et al., 2011; 11. Sopha et al., 2013; 12. Walzberg et al., 2017; 13. Natarajan et al., 2011; 14. Allen et al., 2019; 15. Hicks and Theis, 2014; 16. Hicks et al., 2015; 17. Jensen and Chappin, 2017; 18. Zhang et al., 2011; 19. Mueller and de Haan, 2009 and de Haan et al., 2009 (one study, publication split in two parts); 20. Silvia and Krause, 2016; 21. Bleda and Valente, 2009; 22. Lamperti et al., 2018; 23. Monasterolo and Raberto, 2018; 24. Rengs et al., 2020; 25. Herrmann and Savin, 2017; 26. Monasterolo and Raberto, 2016; 27. Ponta et al., 2018; 28. Safarzynska and van den Bergh, 2017a; 29. Beckenbach et al., 2018; 30. Isley et al., 2015; 31. van der Vooren and Brouillat, 2015; 32. Veit et al., 2009; 33. Chen et al., 2013; 34. Tang et al., 2015; 35. Matsumoto, 2008; 36. Lee and Han, 2016; 37. Niamir et al., 2018; 38. Gerst et al., 2013. 39. D'Orazio and Valente, 2018; 40. Eppstein et al., 2011; 41. Richstein et al., 2015; 42. Chen et al., 2018; 43. Desmarchelier et al., 2013; 44. Kraan et al., 2018; 45. Li and Strachan, 2017; 46. Richstein et al., 2014; 47. Tang et al., 2017; 48. Wu et al., 2018; 49. Zhu et

al., 2018; 50. Zhu et al., 2016; 51. Nannen and van den Bergh, 2010; 52. Hofer et al., 2018; 53. Irsyad et al., 2019; 54. Köhler et al., 2009; 55. Kowalska-Pyzalska, 2016; 56. Lee et al., 2014; 57. Schröder and Wolf, 2017; 58. Azar and Menassa, 2011; 59. Damiani and Sissa, 2013; 60. Chappin and Dijkema, 2009. 61. Safarzynska and van den Bergh, 2018.

The most common non-optimizing rules consumers employ are: (i) a threshold rule, e.g. choosing an option if its utility exceeds a certain threshold; (ii) sticking to a previously chosen option (due to habitual behaviour or a default choice); and (iii) imitating choices made by others. Less common alternatives include: stochastic factors, such as taking a decision with a certain probability; using a step-wise decision process, i.e., simplifying a decision problem by splitting it into parts; or exhibiting loss aversion. For example, in deciding between house heating alternatives (Sopha et al., 2011), some agents select the option that is the most popular among their peers (imitation); others just stick to the default choice; and again others follow a two-step decision process, first selecting the most popular option among their peers and then deciding whether to switch to it.

Other models assume consumers to maximise utility but without taking into account all available information. In these cases, agents limit their attention to a subset of available choices or display limited awareness about some aspect of the choice environment. For example, in Mueller and de Haan (2009), in deciding which car to purchase, agents radically reduce their initial choice set of more than 2000 cars using a rule that ignores most of car characteristics. In Niamir et al. (2018), consumers' investment in a renewable energy technology depends on their awareness of the relation between burning fossil fuels and climate change, while in Bleda and Valente (2009) consumers only focus on two of multiple characteristics when choosing between high- and low-carbon products.

Turning to studies with firms as agents, bounded rationality comes most often in the form of imperfect information and myopia. That is, when forming expectations about future prices, firms tend to ignore relevant information that would contribute to more accurate expectations and, hence, better decisions. Regarding myopic behaviour, a variety of cases were found. For example, in Lee and Han (2016) firms seek short-term gains, and in Ponta et al. (2018) they are assumed to make short-term production plans based on past-sales, i.e. without properly forming expectations regarding future sales. In a few models, firms are assumed to only consider a subset of all available choices due to their inability to consider the full choice set, in a similar way as consumers. Lastly, in Lamperti et al. (2018) firms are assumed to decide once and for all about a fixed amount to spend on R&D, i.e. to never update it on the basis of feedback about investment consequences in later periods.

In several studies firms employ non-optimizing rules. A frequent assumption is that firms seek profits while using mark-up pricing, a heuristic rule to add a certain percentage of the cost of a product to determine its sales price. Another type of bounded rationality often used is firms employing a stochastic rule in their decision process. To illustrate, in Veit et al. (2008), electricity producers compete by setting their bid to enter the market: instead of always equalling it to the true marginal cost, they randomly choose among an experienced-based choice set. A study by Matsumoto (2015) uses an imitation rule in describing an emissions trading market, where firms base their future strategy on other firms' predictions. In Bleda and Valente (2009) producers invest in R&D only when competitors' market share passes a certain threshold value.

It is worth mentioning that whenever banks are explicitly modelled as agents they are assumed to act rationally (Rengs et al., 2020; Monasterolo and Raberto, 2016; Ponta et al., 2018; Safarzynska and van den Bergh, 2017a; Gerst et al., 2013). Governments on the other hand are sometimes described as boundedly rational, namely in three cases: Nannen and van den Bergh (imitating decisions of other governments); Isley et al. (myopia regarding future carbon prices); and Natarajan et al. (arbitrary settings of subsidies not accounting for positive externalities).

Finally, only a minority of studies (about a quarter) in the sample develop models that incorporate more than one dimension of bounded rationality. In reality, however, agents – whether individuals or firms – tends to be boundedly rational in multiple ways: for example, information is seldom complete, behavior is most of the time habitual, and people tend to be loss averse in a wide range of situations. Among the reviewed studies that combined bounded rationality dimensions, 10 out of 46 studies describing consumers, and 9 out of 31 describing firms. The most common combination for both is imperfect information and some non-optimizing rule (limited awareness, myopia, etc.). To illustrate,

Ernst et al. (2017) assume consumers to have limited awareness (imperfect information) as well as status quo bias.

5.3 Social interactions and networks

ABMs frequently describe social interactions in terms of information exchange or behavioural spillovers. Social interactions can be considered to endogenise preferences or information of agents. For example, in McCoy and Lyons (2014) the utility of using an electric vehicle increases with the share of adopting peers; or in Kangur et al. (2018) agents rely on their peers to gather information about characteristics of electric vehicles. Agents usually interact in an explicit social network. Psychologically more complex behaviours are more common in models with a limited scope, such as describing the adoption and diffusion of a single option – e.g., an electric vehicle or solar PV on one's roof (Natarajan et al., 2011; Silvia and Krause, 2016; Schröder and Wolf, 2017; Kangur et al., 2017; Irsyad et al., 2019). On the other hand, ABM studies describing the entire economy tend to include simpler behaviours (Monasterolo and Raberto, 2016; Lamperti et al., 2018). In terms of distribution among themes, most studies on product/technology diffusion and energy conservation include social interactions (15 out of 21 and 11 out of 15, respectively) while most studies on emissions reduction have a broader scope and tend to omit such interactions (only 6 out of 25 include such interactions).

Several types of interactions are addressed by the reviewed ABMs. The simplest form is information diffusion: social connections provide information about the existence of a new good - a necessary condition for its adoption as in Jensen and Chappin (2017). Information can diffuse through a word-of-mouth network that helps the agents to revise their expectations about the utility associated with a certain behaviour (Azar and Menassa, 2011; Niamir et al., 2018; Ernst and Briegel, 2017; Silvia and Krause, 2016; Wang et al., 2018a; Kangur et al., 2018). The information can also be negative, slowing down product diffusion. For example, in Wang et al. (2018a), the expected revenue of installing solar PV is negatively influenced by information from neighbours about risks of malfunctioning or damages.

Social interactions can affect the formation of preferences. The likelihood – or the utility – of adopting a behaviour can increase with the number of connections that have already adopted (Natarajan et al., 2011; Damiani and Sissa, 2013; McCoy and Lyons, 2014; Hicks et al., 2015; Palmer et al., 2015; Rai and Robinson, 2015; Kowalska-Pyzalska, 2016; Wang et al., 2018a; Rengs et al., 2020). Agents can also conform to average behaviour in the population through so-called global interactions (McCoy and Lyons, 2014; Allen et al., 2018). A last mechanism modelled is status seeking, linking the consumption of low-carbon goods and a positive social image (Nannen and van den Bergh, 2010; Rengs et al., 2020). In this respect, it is worth noting that the adoption of a good by an agent is sometimes also modelled as having a negative effect on the likelihood that other agents will adopt it: this so-called "snob effect" influences agents in Safarzynska and van den Bergh (2017a) and Rengs et al. (2020) to buy unpopular goods.

Non-market interactions between firms tend to run through the channel of imitation: heterogeneous firms explore different strategies and the most successful ones are imitated by the others (Bleda and Valente, 2009; Matsumoto, 2008; Gerst et al., 2013; Beckenbach et al., 2017; Rengs et al., 2018; Isley et al., 2018). For example, in Gerst et al. (2013) and Beckenbach et al. (2017), firms can split R&D expenditures between innovation and imitation. Both are considered to be risky strategies and not necessarily successful. Imitation can be restricted only to happen between certain firms, depending on their technological similarity (Gerst et al., 2013) or their maturity (Beckenbach et al., 2017). Heterogeneous absorptive and imitation capacities across firms then influence the diffusion rate of a new low-carbon technology. The older literature on firms and innovation already recognized interaction between firms as a determinant of firm strategies (Nelson and Winter, 1982; Lieberman and Asaba, 2006). Such endogenous selection of strategies can give rise to path dependence (Zhang et al., 2011; Rengs et al., 2020; Zhu et al., 2018). Representing imitation and technology diffusion between firms allows one to study such path dependence and other barriers to a technological transition (Hötte, 2019).

The reviewed ABMs describe different network topologies: random networks characterized by a short average distance between any two agents (Kowalska-Pyzalska, 2016; Walzberg et al., 2017);

regular networks characterized by a high clustering (Desmarchelier et al., 2013; Niamir et al., 2018); small-world networks which combine short average distance and high clustering (Sopha et al., 2011; McCoy and Lyons, 2014; Rai and Robinson, 2015; Palmer et al., 2015; Moglia et al., 2018); and scale-free networks displaying a highly asymmetric degree distribution with a few well-connected agents (Nannen and van den Bergh, 2010; Eppstein et al., 2011; McCoy and Lyons, 2014; Wang et al., 2018a).

Small-world and scale-free topologies serve as stylized representation of physical and digital interactions, respectively. Small-world networks are mainly used to describe interactions leading to the adoption of home-specific goods – such as solar PV in Rai and Robinson (2015) or heating technology in Sopha et al. (2011) – while scale-free networks are more suited to study information diffusion in online social networks, such as in Wang et al. (2018). Only one reviewed study compares network topologies to find the best structure for promoting the diffusion of a low-carbon good (McCoy and Lyons, 2014). Comparing small-world and scale free topologies, they find that the former is the most effective for the diffusion of electric vehicles. Empirical or geographical networks are also considered (Eppstein et al., 2011; Palmer et al., 2015, Silvia and Krause, 2016; Schröder and Wolf, 2017; Kangur et al., 2017; Ernst and Briegel, 2017). Here, agents are assumed to interact with similar individuals, which reflects the homophily property that frequently characterizes social networks in the real world.

6. Climate policies in the reviewed studies
6.1 Policy objectives, instruments and scenarios
In terms of policy objectives, one can make a basic distinction between studies focusing on either single or multiple policy objectives. Important ones in the first group are emission reduction (e.g., Tang et al., 2017), energy use reduction more directly (Hicks et al. 2014), and adoption and diffusion of low-carbon/energy technologies (e.g. Silva and Krause 2016; Kowalska-Pyzalska 2016; Ernst and Briegl 2017). The second group has a variety of additional policy objectives, such as reducing fossil fuel use while maintaining social welfare (Nannen and van den Bergh, 2010), reducing price volatility, total generation costs and consumer expenditures (Richstein et al. 2014), economic efficiency (Beckenbach et al. 2017), or correcting market failures in the credit market (Monasterolo and Raberto, 2016). Other side-objectives include minimizing distributive effects (Monasterolo and Raberto, 2018), encouraging employment (Rengs et al., 2020), maximising long-term benefits compared to short-term costs (Ponta et al., 2018), or spurring technological innovation (Bleda and Valente, 2009; Isley et al., 2015).

ABM studies have examined a variety of policy instruments. Table 4 provides an overview for the three themes and associated sub-themes. The most common are market-based instruments, such as carbon taxation and trading (e.g. Richstein et al., 2014; Li and Strachan, 2017) or a more general carbon price (e.g. Kraan et al., 2018). These are particularly prominent in the theme of emissions reduction. Another group of instruments are subsidies, which can be found in all themes and which come in two types, namely adoption subsidies aimed at stimulating the deployment of new products or technologies (e.g. Kangur et al., 2017), and innovation subsidies aimed at encouraging R&D into low-carbon products and process technologies (e.g., Hermann and Savin, 2017). Certain studies examine 'command-and-control' instruments such as a ban on old, dirty cars (e.g. Hofer et al., 2018). A number of studies, particularly in product/technology diffusion and in energy conservation, test different types of information provision, such as distinctly framed information campaigns (Schröder and Wolf, 2017), or interventions taking advantage of the social network, such as providing for free low-carbon/energy products to well-connected individuals (Jensen et al., 2017). Finally, a number of studies examine rather unusual, sector-specific policy interventions, such as motivating salespeople to give recommendations of energy-efficient products (Moglia et al., 2018).

Table 4. Frequency of policy instruments by application area (cf. Table 1) in the reviewed studies

Themes (# studies)	Policy instruments	Studies
Emission reduction (25)	Taxes (11)	Gerst et al., 2013; Chen et al., 2013; Van der Vooren and Brouillat, 2015; Isley et al., 2015; Monasterolo and Raberto, 2016; Li, 2017; Li and Strachan, 2017; Kraan et al., 2018; Wu et al., 2018; Monasterolo and Raberto, 2018; Rengs et al., 2020
	Emissions trading (11)	Matsumoto, 2008; Chappin and Dijkema, 2009; Richstein et al., 2014; Richstein et al., 2015; Tang et al., 2015; Isley et al., 2015; Zhu et al., 2016; ; Lee and Han, 2016; Beckenbach et al., 2017; Tang et al., 2017; Zhu et al., 2018;
	Subsidies (6)	Gerst et al., 2013; Richstein et al., 2015; Tang et al., 2015; Beckenbach et al., 2017; Rengs et al., 2020
	Command-and-control (3)	Van der Vooren and Brouillat, 2015; Beckenbach et al., 2017; Hofer et al., 2018
	Rebates/feebates (2)	Mueller and de Haan, 2009; Van der Vooren and Brouillat, 2015
	Financing instruments (2)	Monasterolo and Raberto, 2016; Monasterolo and Raberto, 2018
	Policy mix (2)	Van der Vooren and Brouillat, 2015; Hofer et al., 2018
	Other (6)	Veit et al., 2009; Chen et al., 2013; Li and Strachan, 2017; Hofer et al., 2018; Lamperti et al., 2018; Rengs et al., 2020
Product/technology diffusion (21)	Subsidies (6)	Natarajan et al. 2011; Silvia and Krause, 2016; Herrmann and Savin, 2017; Safarzynska and van den Bergh, 2017a; Kangur et al. 2017; Safarzynska and van den Bergh, 2018; Irsyad et al. 2019
	Information provision / marketing (6)	Bleda and Valente; 2009; Nannen and van den Bergh, 2010; Sopha et al. 2011; Desmarchelier et al. 2013; Ernst and Briegel, 2017; Wang et al. 2018a
	Feed-in-tariffs (4)	Palmer et al. 2015; Herrmann and Savin, 2017; Ponta et al. 2018; Irsyad et al. 2019
	Taxes (4)	Nannen and van den Bergh, 2010; Eppstein et al. 2011; Desmarchelier et al. 2013; Kangur et al. 2017
	Infrastructural policies (2)	Silvia and Krause, 2016; Kangur et al. 2017;
	Rebates/feebates (3)	Eppstein et al. 2011; Rai and Robinson, 2015; Wang et al. 2018a
	Other financial incentives (2)	Palmer et al. 2015; Irsyad et al. 2019
	Financing instruments (3)	Safarzynska and van den Bergh, 2017a; D'Orazio et al. 2019; Irsyad et al. 2019
	Other (10)	Köhler et al. 2009; Natarajan 2011; Sopha et al. 2011; Sopha et al. 2013; Desmarchelier et al. 2013; McCoy and Lyons, 2014; Silvia and Krause, 2016; Safarzynska and van den Bergh, 2017a;; Chen et al. 2018; Wang et al. 2018a
Energy conservation (15)	Information provision / marketing (6)	Zhang et al. 2011; Azar and Menassa 2011; Kowalska-Pyzalska 2016; Jensen and Chappin, 2017; Schröder and Wolf, 2017; Moglia et al. 2018
	Subsidies (5)	Lee et al. 2014; Hicks and Theis, 2014; Hicks et al. 2015; Moglia et al. 2018; Safarzynska and van den Bergh, 2018
	Taxes (2)	Lee et al. 2014; Hicks et al. 2015
	Other financial incentives (3)	Azar and Menassa 2011; Moglia et al. 2018; Wang et al. 2018b
	Smart meters (2)	Damiani and Sissa, 2013; Walzberg et al. 2017
	Other (5)	Zhang et al. 2011; Lee et al. 2014; Moglia et al. 2018; Niamir et al. 2018; Allen et al. 2018

Note: Policy instruments may add up to more than the number of papers per category because certain studies test multiple instruments.

Some ABMs develop scenarios around a single policy instrument and compare these against a no-policy or business-as-usual scenario. For example, a single policy instrument like a carbon tax is tested under

various assumptions, e.g. whether the price is stable over time or not (Li, 2017). Another example is that different information campaigns are studied (Schröder and Wolf, 2017). It is more common, though, that several isolated instruments are tested, giving rise to multiple scenarios. A small number of studies examine combinations of policy instruments with the particular aim to uncover synergetic effects of reinforcing or moderating nature (e.g. Silvia and Krause, 2016; Hofer et al., 2018). It is worth noting, though, that some of the ABMs that lack policies address other types of scenarios. Examples are testing price incentives when assuming homo- versus heterogeneous demand responses (Wang et al., 2018b) or increasing the agents' behavioural complexity from rational to boundedly rational (e.g. Niamir et al., 2018).

Several macroeconomic ABMs are designed to address interdependencies between very distinct markets, e.g. for electricity, labour and financial services, to explain connections among unemployment, inequality, financial stability, technological progress and environmental problems (Safarzynska and van den Bergh, 2017a[3]; Monasterolo and Raberto, 2016; Lamperti et al., 2018). It is informative as well to consider which markets have been modelled for which policy interventions. Most common in the reviewed studies is the combination of a carbon market with the policy of emissions trading (11 cases), which is rather trivial. The impacts of a carbon tax are mostly studied using generic consumption goods markets or capital markets (7 and 6 cases, respectively), whereas subsidies are often found together with generic consumption and electricity markets (4 and 6 times). Electricity markets are frequently modelled to study subsidies, feed-in-tariffs or carbon trading. Studies with "soft measures" like information campaigns consider how these affect diffusion in consumer good, energy or electricity markets. Labour markets appear with a number of policy instruments, including carbon taxes, subsidies, feed-in-tariffs, regulation and monetary policies, but not with any policy mix. Table 5 summarises the frequency with which markets and policy types appear together.

Finally, six of the reviewed studies give attention to energy rebound (de Haan et al., 2009; Azar and Menassa, 2011; Hicks and Theis, 2014; Hicks et al., 2015; Walzberg et al., 2017; and Safarzynska and van den Bergh, 2018). Most of these do not assign it a main role. Exceptions are Walzberg et al. (2017) and Safarzynska and van den Bergh (2018). The first measures rebound as the difference in pre- and post-energy consumption levels after adoption of smart meters designed to give real time feedback on household energy consumption. The latter assess rebound of energy conservation due to car purchase and use when encouraged through adoption subsidies. This takes into account connections with electricity generation and distinct behavioural assumptions.

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[3] An application of this model to investments in renewable energy is studied in Safarzynska and van den Bergh (2017b).

Table 5. Frequency of specific combinations of markets and policy instruments

	Rebate/ Feebate	Subsidy	Feed-in-tariff	Carbon tax	Emission trading	Other financial incentives	Regulation	Infra-structure	Information provision/ Marketing	Financial instruments	Smart meters	Other	Policy mix
Capital market	0	2	1	6	0	0	0	0	0	2	0	3	0
Carbon (permit) market	0	1	0	1	11	0	0	0	0	0	0	1	0
Generic consumption good	0	4	1	7	3	0	0	1	2	4	0	5	0
Specific consumption, energy generation	1	2	2	0	0	1	0	0	2	1	0	5	1
Specific consumption, vehicles	3	1	0	2	0	0	1	0	0	0	0	1	1
Electricity	0	6	4	2	5	2	1	0	1	2	0	5	1
Energy, other	0	2	0	3	0	1	0	0	2	0	0	2	1
Financial market	0	1	1	2	0	0	0	0	0	4	0	2	0
Labour market	0	1	1	2	0	0	0	0	0	3	0	1	0
Other markets	0	1	1	1	0	0	0	0	1	0	0	0	0
Raw material markets	0	1	1	2	1	0	0	0	0	3	0	1	0

Note: Darker colour of a cell indicates a higher number of studies.

6.2 Insights about climate policy

Here we give an impression of research results for the main climate policy instruments studied, namely carbon taxation and trading, subsidies and feed-in-tariffs, information provision, and instrument combinations. In view of the huge diversity of model assumptions and lack of comparable studies, it is not possible to perform a systematic assessment of the performance of policies across different model settings. How this might be done is further discussed in Section 7 on future research.

A total of 17 out of the 65 reviewed studies analyse a carbon or other tax (e.g. a fossil fuel tax). Carbon taxes are found to reduce emissions quickly, especially compared to subsidies to encourage energy-saving technologies (Lee et al. 2014) or information provision (Desmarchelier et al. 2013). With respect to employment, carbon taxes perform worst when revenues are spent on green procurement or adoption subsidies and best when they are used to cut labour taxes (Rengs et al. 2020). Unemployment is found to be higher and capital accumulation lower compared to green bonds when carbon taxes are in place (Monasterolo and Raberto 2016, 2018). In Gerst et al. (2013) the recycling mechanism does not seem to affect the level of emissions reduction. Isley et al. (2015) on the contrary find that long-term decarbonisation is strongest when revenues are directed to firms because this will reduce lobbying pressure against effective policy. A study by Chen et al. (2013) finds that a carbon tax can decarbonise the energy system but may also reduce total energy generation, which can cause overall carbon intensity to increase as installed capacity of coal plants is only reduced up to a limit, involving some old power plants to remain active for longer.

A total of 25 studies include some form of subsidy in their policy analysis. While carbon taxes are often studied in a macro-economic setting, subsidies and feed-in-tariffs are more frequently analysed using models with a partial scope. A macro-ABM study by Rengs et al. (2020) find that price levels rise stronger if carbon tax revenues are used for innovation subsidies compared to other policies, such as green government procurement or revenue recycling through labour tax cuts or an innovation subsidy. Sopha et al. (2013) show that if functional reliability is important to heating, then high subsidies have little impact on the adoption of low-carbon technologies (heating technology in this specific case). A study by Kangur et al. (2017) finds that financial and environmental considerations are almost of equal importance to consumers when deciding to buy an electric vehicle. Heterogeneity among households matters for the effectiveness of subsidies as well. Eppstein et al. (2011) demonstrate that even under a subsidy only early adopters buy plug-in hybrid vehicles (PHEVs) during initial years when the technology has become available. Silvia and Krause (2016) confirm, also for the PHEV market, that subsidies usually only trigger those agents who would have adopted in any case. For households who are more sensitive to prices, subsidies can be very effective, as Irsyad et al. (2019) show for solar PV adoption in developing countries. A study by Safarzynska and van den Bergh (2018) finds that ignoring realistic car purchase and associated use behaviours of consumers leads to overly high expectations about diffusion of clean-vehicle subsidies and thus underestimates emissions from passenger cars. In an ABM for renewable electricity technologies in Germany, Herrmann and Savin (2017) find evidence that feed-in-tariffs (FITs) granted over the lifetime of a renewable energy technology can promote a quick diffusion process, but point out that this can also create lock-in of technologies that are not necessarily the most desirable ones in the long run. Effectively, such a lock-in effect of subsidies comes down to a disincentive of certain alternative low-carbon technologies (Chen et al., 2013; Lee et al., 2014).

Eleven models in the sample examine emissions trading in a carbon market. Interactions with other macro-economic markets are not often considered by these models. A notable exception is Tang et al. (2017), who find that carbon markets cause a reduction in both emissions and GDP, with the magnitude of these impacts depending on the auctioning mechanism. Other exceptions are Isley et al. (2015) and Richstein et al. (2014). Studying a combination of emissions trading, standards and research subsidies, Beckenbach et al. (2017) find that relatively high permit prices with relatively low standards result in the lowest emissions, while subsidies have little impact. Zhu et al. (2018) show that introducing

boundedly rational agents to a carbon market can reproduce a pattern that is also observed in reality, namely that a permit price first overshoots the equilibrium value and then gradually declines. Lee and Han (2016) employ ABM to examine the costs of finding and selecting a suitable trading partner within a population of potential traders. They show that high transaction costs reduce the speed with which permit prices converge to a final price.

Information provision is tested by various studies. For example, Ernst and Briegel (2017) examine diffusion of green electricity in Germany and find that an information campaign has little effect at first, but becomes more effective once an external event (Fukushima disaster) increases pro-environmental orientations. Schröder and Wolf (2017) demonstrate that a media campaign, depending on how it is precisely framed, can increase preferences for car-sharing up to 35%, compared to 8% in a baseline scenario without policy. Another prominent information-based strategy is eco-labelling, studied by Desmarchelier et al. (2013). Their results suggest that when imitation is easy, eco-labelling may lead to the disappearance of niche markets for most low-carbon goods, thus having a surprisingly negative effect. They suggest that the label increases the salience of the environmental characteristic and - given that a majority of agents has non-environmental preferences – ultimately leads to a contagious decrease in environmental preferences. In contrast, a study by Bleda and Valente (2009) finds that especially graded labels – i.e. products rated on energy efficiency from very low to very high, rather than binary (e.g., clean vs. dirty) – are effective, as they allow for more precise discrimination of the products. One needs a very detailed behavioural module as in an ABM to test such subtleties. The study finds that graded labels further increase competition for environmental quality on the firm side and encourage environmental innovation. Somewhat distinct information-based instruments are social network interventions. For instance, Jensen et al. (2017) show that targeting opinion leaders to communicate about smart meters has a considerable effect on the diffusion of this new technology (see also Wang et al., 2018a). Similarly, Nannen and van den Bergh consider a policy that increases the relative welfare of exemplary agents, who invest much in renewable energy, by awarding them a monetary prize. Given that awards have to be paid out of income taxes, they find there is an optimal number of awards in terms of its the effect on the overall share of renewable energy.

An issue that has received fairly little attention in ABM studies is how policies work in combination. One study examines how electric vehicles diffuse and combines three policies in one scenario: subsidies, an extension of the charging network, and governmental purchase of vehicles. It finds that combining policies leads to the highest number of adopted vehicles when compared to scenarios with isolated policies at higher stringency (Silvia and Krause, 2016). Similarly, Herrmann and Savin (2017) show that combining R&D subsidies early on, and subsidies to final consumers at a later stage, produces complementary effects in terms of diffusion of renewable energy technologies. It allows more customers to afford improved technologies and exploits the willingness-to-pay for these by high-income customers. A study by Hofer et al. (2018) shows that a combination of three transport policies aimed at reducing urban car emissions yields a slightly lower effect than adding the impacts of each policies in isolation, due to synergies. Some studies suggest that a combination of carbon taxes with other policies can create synergetic effects in reducing emissions (Eppstein et al., 2011). As previously mentioned, policies may also be offsetting, which is why studying instruments in combination is important. However, as it is difficult to achieve synergies on all relevant policy criteria such as technology adoption and minimizing public expenditures, van der Vooren and Brouillat (2015), in their model on the car market, suggest combining policies with different foci, such as a sales tax on CO_2 emissions and a rebate for low-carbon vehicles.

6.3 Illustrating the link between model features and policy results

Given that we review 61 ABM studies that show a lot of diversity in themes, policies and model set-up, it is difficult to generalize about the relationship between model choices regarding components,

specification or parameters values on the one hand, and outcomes of analysis of policy instruments on the other. Instead, we illustrate this relationship for two particular studies.

The first was published in two parts (Mueller and de Haan 2009; de Haan et al., 2009). It describes the purchase of new passenger cars with multiple attributes (2089 versions varying in size, engine power, fuel type, emission characteristics, price, etc.) by consumers (40 groups varying in socio-demographic features) in Switzerland as a two-stage boundedly rational decision-making process: individual choice sets are constructed based on previously owned cars; and alternatives are selected using a multi-attributive weighting rule. Decisions involves the perception of money based on prospect and mental accounting theories, resulting in, among others, gains and losses being reference-dependent, and consumers being more sensitive to fees than to rebates of the same magnitude (reflecting loss aversion). Inclusion of these details of bounded rationality, possible due to the ABM approach, cause model predictions to be closer to observed market outcomes than those of traditional models. The model can study detailed policies under differentiated consumer segments and for a wide range of technical car features. This involves comparing a measure of forecasted new passenger car sales under reference (business-as-usual) and policy simulations. The specific policy studied is a feebate[4] system developed around an energy-labelling scheme with seven categories, ranging from (A) very fuel-efficient cars receiving a cash incentive to (G) highly inefficient cars paying a fee. This stimulated different choices – such as a smaller car, lighter engine or lower-carbon fuel type – depending on the price-sensitivity and behavioural features of consumers. An incentive of €2000 for A-labelled cars induces a 3.4% to 4.3% reduction in CO_2 emissions associated with new cars versus the reference scenario.

The results indicate high policy effectiveness with limited utility loss due to switching to a less powerful engine, due to utility gains in terms of car price, fuel costs and rebate; and what the authors call "low market disturbance", meaning few consumers feeling compelled to switch to a smaller car. Both outcomes result from the ABM approach allowing for very detailed choice sets containing within-model technical diversity. The study suggests that jointly, these model features contribute to more realistic predictions and more optimistic policy outcomes than with traditional models, in the sense that consumers have more options or flexibility to reduce emissions. As a result, emissions reduction is achieved with less drastic direct impacts on individuals' welfare. Whether this is representative is worthwhile to study further, as it might suggest that ABM studies provide a more optimistic view on the overall effects of climate policy. This notably requires the use of macro ABMs, as the above discussed study adopted a partial angle and therefore did not account for wider welfare impact through use of public budgets nor likely rebound effects of feebates (Adamou et al., 2014; d'Haultfoeuille et al., 2014).

A second example is a study by Wang et al. (2018a), which illustrates another advantage for policy analysis of ABMs, namely social networks. The study models the diffusion of solar PV in a social network where agents observe the popularity as well as the technical failures of solar PV in their neighbourhood. Based on this information, they form their expectations about financial gains, including reparation costs in case of a technical failure, and arrive at an adoption decision. Agents are biased when assessing the probability of a technical failure happening (bounded rationality) and uncertain about its reparation costs. This leads agents to overestimate the probability of damages and therefore expected reparation costs. The study tests five policies to determine which is the most cost-effective to promote the diffusion of solar PV panels: rebate policy; free insurance against damages; an information

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[4] Feebates combine fees for products with relatively bad environmental performance with a rebate or subsidy for products with relatively good environmental performance. The instrument is self-financing if the cost of the rebates is paid from the revenues of the fees.

campaign; information screening[5]; and communication enhancement[6]. It finds that the cost-effectiveness of a policy depends on the share of adopters at the time of policy implementation. In a first phase of diffusion with a still low share of adopters, the reliability of solar PV panels and reparation costs are main obstacles to adoption, contributing to free insurance[7] of solar PV panels by the government, by reducing uncertainty and countering diffusion of negative information, being more cost effective than the rebate. As solar PV panels become more popular, uncertainty is not a dominant factor anymore and social influence (i.e. imitation) becomes the main driver of adoption, thus reducing the benefits of an insurance. Therefore, in a second phase of diffusion, the rebate is more cost-effective.

This study illustrates well that the ABM approach has as an advantage that its description of social dynamics underlying consumer decisions allows determining the most cost-effective policy to promote solar PV panels in distinct phases of the diffusion process.

7. Model challenges and further research

From the review we derive various challenges that ABM studies face. A first thing we noted is that the description of the reviewed models is often incomplete and lacks coherence. Some papers refer to earlier studies for more details, but often do not specify the exact differences and similarities. This makes it difficult to judge or replicate studies. On the other hand, many models are documented very well. We want to highlight Bleda and Valente (2009), Eppstein et al. (2011) and Zhu et al. (2018). A stronger focus on standardisation in presentation and assumptions of ABMs would be welcome as it would contribute to transparency and comparison. Several authors have already proposed protocols for describing or reporting ABM based studies, such as the (extended) ODD protocol (Grimm et al., 2006; Müller et al., 2013). Although these could contribute to harmonization across studies, they are rarely employed. Wolf et al. (2013) provide additional guidelines.

A second challenge is that ABMs tend to be complex. This confounds the assessment of simple causes behind specific effects in the results. In this respect, modellers face a trade-off between scope and detail. Models of an entire economy or interacting countries tend to considerably simplify certain model elements that are often dealt with in greater detail in models of a specific market or technology. The main advantage of the macro models is that they address interactions between multiple markets. For instance, the studies by Ponta et al. (2018) and Herrmann and Savin (2017) both address the role of a feed-in tariff, but with very different model scopes. The trick of simplifying models comes down to making the right choices for the policy problem at hand. To illustrate, an exogenous demand curve as in Chen et al. (2013) is debatable as the model explores long-term effects of policies. The challenge of developing useful ABMs for climate policy comes down to optimizing model complexity. This requires making a trade-off between model inadequacy, due too many simplifying assumptions, and model propagation errors, due to too much model complexity (Saltelli, 2019).

Observing the reviewed studies and their policy features, we provide some ideas for further research applying agent-based models to climate policy. An old theme in climate policy is whether carbon pricing is best achieved through a tax or market. Here attention is lacking for the role of behaviour by agents. According to Shogren (2012), markets may select better for rationality, i.e. rational behaviour survives and is replicated more, meaning that effective and cost-effective outcomes are more likely under carbon markets than taxes. As the reviewed ABM studies do not address this topic, future ones might test this, by comparing how the two types of carbon pricing perform in terms of effectiveness of emissions reduction under bounded rationality of, and social interactions among, consumers and producers.

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[5] Information screening means that the government promotes that consumers share positive information.
[6] Communication enhancement is a social network policy. It is modelled as an increase of the average degree in the network (i.e. the average number of peers of the agents), fostering the exchange of information about the new technology.
[7] The government provides a free insurance covering the cost associated with damage to solar PV panels.

The reviewed macroeconomic ABMs study distinct policies and policy mixes. But they have not much contributed to the long-standing debate on a double dividend (e.g., positive effects on employment and emissions reduction) of an environmental tax reform, i.e. shifting taxes from labour to carbon (Goulder, 1995). This could add more insight about the particular role of bounded rationality and social interactions, as well as the role of low-carbon innovation, which are missing in conventional general equilibrium studies that dominate this topic. Since ABMs describe multiple agents and heterogeneity, they are also well suited to address the role of inequality in relation to environmental tax reform.

Next, the study of information provision strategies in climate policy is difficult in traditional equilibrium models but more straightforward in ABMs. Indeed, we find that several ABM studies in our review addressed this issue, particularly in the theme of energy conservation. However, they do not span the full scope of relevant instruments: information campaigns (targeting very distinct population groups), green awards, the role of traditional versus Internet-based social media, and regulation of advertising of high-carbon goods and services deserve attention as well. Additional research employing ABM could test whether it is more effective for emissions reduction to stimulate low-carbon alternatives through social marketing or discourage high-carbon ones by limiting commercial advertising. This can learn from the few available ABMs of impacts of private and social marketing campaigns, which do not address climate issues (Delre et al., 2007; Perez-Mujica et al., 2014).

Since it cannot be excluded that a transition to a low-carbon economy will involve fundamental changes in lifestyles and culture, it is pertinent to study the impact of a combination of climate policy and changing social norms on lifestyles. While ABMs are capable of studying changes in norms, lifestyle and culture, which has received some attention in other areas (Bianchi and Squazzoni, 2015; Jackson et al., 2017), the reviewed ABM studies of climate policy lack attention for this. Using ABM in this respect allows making connections with the emerging field of cultural evolutionary analysis (Davis et al., 2018; Muthukrishna and Henrich, 2019). This invites attention for issues such as exemplary conducts, role models, social movements and appropriate framing of information provision. Generally, ABMs can be used to examine if and how lifestyles change under certain policy mixes. This could test whether fostering the status of low-carbon goods is an option to drive consumption away from carbon-intensive goods and services; or whether stimulating imitation behaviour is a more effective strategy to reduce emissions than stimulating knowledge diffusion; or, whether frugality, simpler lifestyles and low consumption levels diffuse through exemplary behaviours (Creutzig et al., 2018).

To combine the best of both worlds, describing market and non-market interactions in an integrated model structure can contribute to better policy analysis. A distinguishing feature of ABM is that it can address non-market or social interactions over networks. While several of the reviewed ABM studies offer such integrated analysis, they certainly do not cover all possible combination of policy instruments (see Table 5). A more systematic approach could clarify which combination of instruments – such as carbon pricing, innovation and adoption subsidies, and specific types of information provision – assure complementary effects (Wiese et al., 2018). This would provide a solid basis for formulating optimal policy mixes.

Rational-agent approaches dominate the study of energy and carbon rebound. Hence, systematic consideration of how bounded rationality and social interactions, by households as well as firms, affect rebound and what this implies for policy design requires more attention. Few of the reviewed ABM studies have addressed this topic (see references in Section 6.1), and it is worthwhile to invest more into this area as rebound is likely to differ between unbounded and bounded rationality. This requires comparing rebound effects for different rebound mechanisms (intensity-of-use, spending and market effects, diffusion effects and macroeconomic effects), between ABM and other model types.

As noted in Section 5.2, a minority of studies have incorporated in their models more than one aspect of bounded rationality in decision-making for both consumers and firms, even though multiple aspects are more realistic. Moreover, only a small fraction of possible behavioural rules has been implemented

so far. It is therefore useful to explore more systematically the consequences of relevant combinations of bounded rationality. This could test for positive and negative synergy in terms of emissions reduction under the influence of particular climate policies.

Finally, while most reviewed studies examine the effectiveness of policies in reducing emissions – directly or indirectly, as through energy conservation and product/technology diffusion – an equally important feature of policies is their political feasibility, mediated by public opinion. Few ABM studies examine opinion dynamics of agents with regard to climate change and how this affects their voting decisions which translate in political support for, or resistance to, climate policies (Geisendorf, 2016; Kraan et al., 2019). Such studies, however, were not covered in our sample, as they lack a clear policy instrument or connection to emission reductions or product/technology diffusion. Future studies could try to integrate such opinion dynamics in ABM models with policies. This is highly relevant given that worldwide the implementation of climate policy is hampered by a lack of social and political support.

While the present review highlighted only the most noteworthy findings with regard to policy effects, further research could investigate these in a more comprehensive way. This would involve an analysis of policy outcomes in relation to the many distinct model features (e.g. number and types of agents, heterogeneity in behaviour). To do this thoroughly would ideally require a statistical meta-analysis. To achieve this, it would be important to strive for standardization of modelling exercises, as we already noted above, as well as generate ABM studies that more systematically span the relevant space of model features and climate policies.

8. Conclusions

We reviewed 61 studies that employed agent-based models (ABMs) to study climate-energy policies. This focused on three main themes, namely emissions reduction, product/technology diffusion, and energy conservation, and associated sub-themes. Common examples of the latter are carbon and electricity markets, energy-efficiency investments in residential buildings, and diffusion of electric vehicles and renewable energy technologies.

Regarding the first purpose of our review, i.e. identifying the range of choices in the distinct dimensions of ABMs of climate policy, the reviewed studies show a great diversity, not only in terms of applications but also regarding policy focus, types of agents and their behaviour, social interactions and networks, and empirical foundations. Patterns were found to differ between the three themes. To assure realistic and reliable ABMs, the procedures of parametrization, calibration and validation are essential. Most reviewed studies used statistical data and literature values, while some used data from surveys, and only one drew on expert interviews. Future studies are recommended to combine more types of data sources as they cover distinct information necessary to parametrize an ABM. In addition, we suggest providing more clarity in describing the models, allowing for reproducibility, and offering a comparison with general results from traditional model studies.

The second purpose of our review was to collect climate policy features and insights of ABM studies. Compared to traditional models, ABMs allow for more disaggregation which enables them to adequately reflect real-world diversity of individual choices and associated product options. This offers consumers and producers more flexibility in reducing emissions, resulting potentially in less drastic sacrifices in terms of individual welfare. In other words, ABM studies may lead to more optimistic insights about the effectiveness and affordability of climate policy. The current literature is insufficient, though, to conclude about this conjecture as most models in our sample adopt a rather partial perspective on the economy. To address the wider welfare implications, such as related to changes in the (use of the) public budgets and rebound effects, further refinement and application of macro-ABMs for climate policy is recommendable.

Among the policies in our sample, market-based instruments are common, notably carbon taxation and emissions trading. In addition, subsidies receive frequent attention, both ones that stimulate the adoption of products or technologies and ones that encourage innovation research (R&D) by private

enterprises. A surprising policy conclusion is that adoption subsidies may not work as well as suggested by traditional studies, for a number of reasons: adoption subsidies mostly affect early adopters and consumers who are very sensitive to prices; they especially reach agents who would have adopted in any case; and bounded rationality like habits will moderate the effect of subsidies compared to the case of rational behaviour. Very few of the reviewed ABMs assess command-and-control instruments, such as standards, prohibitions or quota. Information provision instruments, like information campaigns or social network interventions, tend to be studied in ABM applications focusing on energy conservation or product/technology diffusion. Their effectiveness remains, though, to be tested in broader macro-economic models. More research is also needed on combining pricing through a tax and permit market, and on mixtures of pricing and information-provision policies. This could assess potential synergies in terms of structural, long-term emissions reduction and describable performance on both effectiveness and distributional consequences. Indeed, good climate policies ideally score well on effectiveness, efficiency and equity. Some of the models addressed only one or two of these performance criteria. In principle, though, ABMs provide a convenient tool to give attention to all three, which is recommendable to offer definite evaluations of climate policies.

We offered various ideas for future research on climate policy using ABMs. One is to compare the performance of carbon taxation and emission trading under different assumptions regarding bounded rationality. This can test the robustness of earlier finding of this type of research. Another is to test whether under bounded rationality environmental tax reform, i.e. shifting taxes from labour to carbon, is more or less likely to create a double dividend, such as in terms of emissions reduction and employment. Next, one could compare information provision strategies in climate policy, such as eco-labels, green awards or information campaigns, to see how effective they are in comparison. Here one might test what works better for emissions reduction: stimulating low-carbon alternatives through social marketing or discouraging high-carbon ones by regulating commercial advertising. ABMs also lend themselves well for studying lifestyle changes. This allows making connections with the emerging field of cultural evolutionary analysis, providing a richer and arguably more realistic picture of what we can expect in terms of fundament changes in consumption patterns. In addition, a distinguishing feature of ABMs is that they can combine market and non-market interactions among agents. This allows examining the potentially complementary nature of policy instruments, notably carbon pricing, innovation and adoption subsidies, technical standards, and various tools of information provision and behavioural diffusion. Finally, ABMs are especially suitable to study opinion dynamics underlying political feasibility of effective climate policies in reducing emissions. More attention for this is pertinent given the political resistance that serious climate policies still face in most countries.

As suggested in Section 7, it is fairly easy to translate the previous research ideas into complex ABM designs. The challenge for ABM studies of climate policy is to strike a right balance of model complexity, by trading-off model inadequacy and model propagation errors. A close connection with empirical or experiment studies on the one hand, and systematic sensitivity analysis on the other, can contribute to relevance and reliability of ABMs for climate policy.

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