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Modelling thermal insulation investment choice in the EU via a behaviourally informed agent-based model

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ABSTRACT

In spite of the established importance that retrofitting the existing building stock has in decreasing end-use carbon emissions and of the large availability of policies aimed at financially supporting renovations, investments in the residential sector remain below the optimal levels. The paper proposes an encompassing theoretical framework that merges economic, behavioural and social motives and suggests diverse policy instruments to promote retrofitting and their appropriate targets. The paper exploits the Consumers Survey data from the Second consumer market study on the functioning of the retail electricity markets for consumers in the EU (2016) to calibrate an agent-based model of the thermal insulation investment choice. The model simulates the investment choice of 19,538 homeowners based on their perceived financial situation and environmental concern, and introduces unobserved networks on which adoption by imitation occurs. We investigate the effect of a financial incentive, a pro-environmental campaign and a norm-based intervention on the adoption rate. Results show that the interplay between economic, behavioural, and social motives produces unexpected outcomes: policies that leverage only one motive are nonetheless affected by the others.

1. Introduction

In 2017, the building stock was responsible for approximately 40% of energy consumption and residential buildings accounted for 25% of CO_2 emissions of the European Union (Tsemekidi Tzeiranaki et al., 2019). The considerable volume of energy consumption and emissions has spurred the EU to raise the 2030 green-house gas emission reduction target to at least 55% compared to 1990 levels as part of the European Green Deal (EC, 2019) and has also inaugurated a new specific strategy targeting the residential sector (EC, 2020). The strategy acknowledges that, in a context where most of the existing buildings in the EU are energy inefficient,[1] it is paramount to promote major modernisation actions including insulation of the building envelope (Boza-Kiss et al., 2021). Nonetheless, such renovations are currently carried out only in 0.2% of the building stock each year (Berger and Höltl, 2019).

In the face of the European Commission objective to double annual energy renovation rate mainly through the retrofit of the existing building stock (Commission, 2020) and of the numerous and diverse supporting measures that have ensued, it is key to understand how to effectively boost the observed suboptimal level of renovations in the EU (Rosenow et al., 2017). The reasons behind such under-investment remain largely unexplained if we rely only on the assumption that households are rational decision-makers (Pollitt and Shaorshadze, 2013), since the cost from non-refundable financial support and low rate loans are usually estimated to be below the savings on energy bills that derive from retrofitting. We explore the hypothesis that investments in energy-efficient technologies – thermal insulation in our study – could be fostered by policies that have a broader theoretical spectrum.

The paper frames the decision to retrofit in the literature on the adoption of technologies and innovates it by claiming that the decision to adopt is better understood by jointly studying economic, behavioural and social motives. While it is plausible to think that any choice is determined by multiple factors, the literature on the diffusion of technology is rather compartmentalised. Traditional adoption models (Mundaca et al., 2010) base the choice on the comparison between costs and benefits. The behavioural economic literature stresses several

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[1] Building stocks built before the appearance of building codes regulating the thermal insulation of the building envelope (Filippidou and Jimenez Navarro, 2019).

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behavioural factors that might affect the decision to adopt a technology (Schleich et al., 2016; Gillingham and Palmer, 2014). Finally, the stream of research initiated by Rogers (2010) assumes that adoption depends on the imitation of early adopters.[2]

We propose an agent-based model (ABM) that exemplifies and encompasses the above-mentioned factors and studies their importance in determining retrofit adoption. The rationale of the analysis, beyond its theoretical interest, is to explore the idea that policymakers should leverage the various factors and be aware of the effects of their interplay, in order to improve the retrofitting rate. To this purpose we start from the theoretical contribution by Bénabou and Tirole (2011b) that, although originally conceived to model individual contributions to the production of a public good, can be amended to analyse energy efficient adoption choices. Furthermore, we extend it to include heterogeneity in social interactions.[3] The model is fed with data from *The Second consumer market study on the functioning of the retail electricity markets for consumers in the EU* (DG-Justice, 2016). In spite of its focus on the electricity sector, the survey is extremely informative for the issues under study in that it covers investments choices of 19,538 homeowners and provides interesting insights into the factors we are interested in, namely the financial situation of the household and its environmental concern. Unfortunately, we do not observe the actual interaction of households and, therefore, we model the imitative process as diffusion on a network Beretta et al. (2018). To study the effect of different types of interaction structures, we simulate centralised and decentralised connections: preferential-attachment and small-world network topology, respectively.

The calibrated model is then used to corroborate the hypothesis that adoption depends on several factors and that including those factors into the toolbox of policymakers can improve the adoption rate of energy-efficient technologies. We show that if a decision were made only on the basis of economic and behavioural motives, the actual adoption rate would be considerably higher than what is observed in our data. Only when we account for imitation, we obtain results more similar to the observed level. We, therefore, conclude that households are not perfectly rational, nor are they entirely driven by pro-social motives. Rather, they make decisions not as isolated agents, but as actors embedded in social relations. In more detail, when decisions are made in isolation, agents decide simultaneously on the basis of their internal states (perceived economic situation and environmental concern). In contrast, when agents interact with each other, adoption slowly takes off and follows the expected S-shaped curve (Rogers, 2010). This has interesting implications for the scope of policy design. Drawing on the recent literature on energy policy measures (see, for example, Bertoldi et al. (2020)) that supports the transition from a subsidy-focused approach to a more diverse portfolio of instruments, we simulated three different types of interventions leveraging economic, behavioural, and imitation motives. Results confirm that enlarging the theoretical framework leads to a more detailed knowledge of the effect of the interventions and leads to reconsidering the design of some established policies. The paper is organised as follows: Section 2 reviews the relevant literature on energy efficiency adoption behaviour, Section 3 describes the theoretical model the setting and specifications of the agent-based model, section 4 illustrates the dataset, and section 5 presents the results of the policy simulation. Finally, section 6 puts results in perspective and discusses their policy implications, and section 7 concludes.

2. Literature review

The analysis is framed in the economic theories that aim at explaining the choice to adopt a technology. The topic is very wide and has been dealt with several approaches. While the empirical literature on the determinants of adoption is vast and offers mixed evidence, we can summarise the theoretical approaches in three broad families. Each stream focuses mainly on one of the following adoption motives: economic, arising from the comparison of cost and benefits and the associated cost savings; behavioural, covering the non-monetary motives driving decisions; and social, stemming from the influence of imitation.

In the economic approach, the decision to invest in energy efficiency is usually depicted as being driven by energy and cost savings motives under capital constraints and full rationality (Gillingham et al., 2009). Therefore, individuals are assumed to be capable of taking into account the benefits that the energy efficiency measure accrues, even though these energy and cost savings are delayed in the future. This implies that rational individuals would always choose to invest in energy efficiency, given that this is economically optimal (McKinsey, 2009), and they might fail to do so due to the way the market is structured (Bertoldi, 2020) .[4] In the behavioural economic approach individuals are seen as rational decision-makers with limited cognitive resources, i.e. boundedly rational individuals (Simon et al., 1955). When making decisions under bounded rationality, they use shortcuts, i.e. heuristics (Tversky and Kahneman, 1974). Sometimes, this might lead to behavioural failures (Shogren and Taylor, 2008), which, in turn, might lead individuals to fail to make optimal decisions, such as investing in energy renovations. These behavioural deviations from rational economic model assumptions are non-standard preferences, inter alia, time, risk, and reference-dependent; non-standard decision-making, such as status quo bias; and non-standard beliefs (DellaVigna, 2009; Schleich et al., 2016; Sorrell and O'Malley, 2004; Della Valle and Bertoldi, 2021). The behavioural economic approach also highlights that, in addition to displaying cognitive deviations, individuals display motivational deviations from rational choice assumptions. In particular, individuals are heterogeneous not only in their preferences, but also in their degrees of self-interest and motivations (Sacco and Zarri, 2003). This heterogeneity in motivations and degrees of self-interest helps explain why some individuals would be willing to invest in energy efficiency even in the absence of benefits or financial incentives that are higher than costs. Some individuals might be willing to invest because they are intrinsically motivated to do so. (Schleich et al., 2016; Bénabou and Tirole, 2011b).

In this case, individuals are considered to display a 'pro-social orientation' (Bénabou and Tirole, 2006): they are motivated to invest because they care about environmental protection.

In the social influence approach, it is held that the choice is also influenced by the surrounding social environment. Deciding whether to adopt a technology is also about taking into account the practices shared with others in the relevant social environment (Wilson et al., 2015). As an example, individuals might decide to renovate because they learn about the behaviour of the peers in the reference group (e.g. social learning (Mittone and Ploner, 2011)). Similarly, they might decide to renovate when they learn that others with similar characteristics have already engaged in that choice (Turner, 2010). Alternatively, they might decide to renovate because they imitate someone who has already engaged in that choice and is satisfied with it (i.e. successful individuals are more likely to be imitated (Apesteguia et al., 2007)). To analyse such influence, it is paramount to take into account the structure of

[2] The literature includes other affecting factors such as, for instance, risk (Ahlrichs et al., 2020) or rebound and prebound effects (Gerarden et al., 2017; Galvin, 2014; Galvin and Sunikka-Blank, 2016). However, the aim of the paper is not to identify specific determinants or behavioural response to energy efficiency measures, but to study broader classes of motives that affect decision-making.

[3] See Chersoni et al. (2021) for a detailed description of the theoretical framework.

[4] Regulatory failures, information asymmetries like split incentives, credit constraints, and imperfect information might prevent individuals to invest (Melvin, 2018; Gillingham et al., 2009).

interaction to identify how information travels and how peers are distributed in the social environment (Beretta et al., 2018).

For what concerns the determinants as identified by the empirical literature, there is clear evidence on the positive effect of income on investing in energy efficient retrofit measures (Schleich, 2019; Trotta, 2018; Nair et al., 2010), including thermal insulation (Urban and Ščasny, 2012). That is primarily related to capital-costs of such investments and with the observation that wealthier households, consuming more energy have more incentives to benefit from the reduction of energy bills through energy efficiency solutions. The literature on the role of environmental concern on adoption decision is variegated,[5] and the empirical evidence is not clear-cut. Environmental concern appears to be significantly less relevant for high-cost energy efficiency investments, suggesting the existence of a trade-off between environmental-friendly behaviours and costs (Trotta, 2018; Whitmarsh and O'Neill, 2010). Conversely, in other studies, it increases the probability of adopting energy efficiency measures (Prete et al., 2017), including thermal insulation (Urban and Ščasny, 2012) and other high-cost technologies, such as photovoltaic systems (Bashiri and Alizadeh, 2018; Bergek and Mignon, 2017). Finally, there exists a vast literature confirming that the choices made by others affect individual decisions. For instance Bandiera and Rasul (2006) shows that farmers' decisions to adopt a new crop depends on the adoption by their network of family and friends. Moreover, colleagues, friends, relatives, and neighbors are viewed as an important and trustworthy sources of information compared to expert advisors (Stieβ and Dunkelberg, 2013; Filippini et al., 2020).

3. Methods

The literature on the adoption of energy-efficient technologies revolves mainly around theoretical models and/or empirical analyses. In our paper, we cover a middle ground in that we start from the theoretical model by Bénabou and Tirole (2011b) but, instead of providing an analytical solution, we simulate it with an ABM calibrated with data. This approach has several advantages. First, it models agents as heterogeneous and autonomous. Individuals make decisions according to their features and as an adaptation to local information. Second, adaptation does not imply maximising behaviour. This is particularly suitable for our topic where households are very diversified and their unresponsiveness to profitable economic investments and incentives seems to exclude the possibility to assume perfect rationality. Third, it allows us to model the environment – social interactions – as a medium separated from the agent. Finally, ABMs allow to retain the theoretical scaffolding of the model and to analyse how it performs when fed with data.

3.1. The theoretical model: Bénabou and Tirole reinterpreted

The decision to invest in energy efficiency is affected by several factors, ranging from inconsistent preferences, to external factors, and non-standard decision-making (Schleich et al., 2016; Sorrell and O'Malley, 2004). When it comes to investing in energy renovation, the decision is even more complex, given that household members associate meanings and symbolic values to their homes, while being affected by the practices shared with their social connections (Wilson et al., 2015). While we acknowledge this complexity of factors, in our study we use a simple specification that encompasses only three main ingredients: i) the agent's extrinsic motivation, representing the sensitivity to a financial incentive depending on a certain perceived financial situation; ii) the agent's intrinsic motivation, representing the degree of pro-social orientation that, in the context of decisions that also benefit the environment, represents the degree of environmental concern; iii) social influence, representing the practices shared with peers in the relevant social environment.

The modelling choice is instrumental to the aim of our study. We want to describe the decision to invest by unifying three theoretical frameworks: the purely economic one, the behavioural economic one and the innovation one. The original model by Bénabou and Tirole (2011b) describes the decision to contribute to the production of a public good. In spite of the different vocation, the model is particularly suitable for our analysis in that it encompasses the three motives of our interest. Therefore, with a few straightforward amendments we can easily apply it to the topic under study[6]: the one-shot decision to invest in thermal insulation. In Bénabou and Tirole (2011b) the decision is influenced by:

- resource cost (to represent economic motives). In our setting, it is a burden that depends on the household's perceived financial situation, i.e., the better the economic status, the lower the burden.
- intrinsic motivation (to represent behavioural motives), i.e., the household's intensity of environmental concern. While environmental concern is often associated with a general intention to act pro-environmentally (Stern, 1992), the paper adheres to the behavioural economic literature that relates environmental concern with an intrinsic motivation to protect the environment as a public good (Brekke and Johansson-Stenman, 2008; Whitmarsh and O'Neill, 2010; Bénabou and Tirole, 2011b), for which individuals internalise the benefits associated to their decision (Achtnicht, 2011).
- social-esteem concern (to represent imitative motives), i.e., reputational cost and benefits deriving from the actors' decision. This factor has undergone the strongest re-interpretation with respect to the original model. In our setting, the social effect on adoption is the propensity to imitate the behaviour of others as in standard epidemic models (Rogers, 2010). In accordance with such models, we assume that when a fraction of the population has already adopted a measure, the adoption by the actor becomes more likely. From our perspective, this is reasonable because, as thermal insulation spreads, adoption might improve due to an increased amount of available information on the technology and knowledge about its functioning, risks and benefits. Moreover, for a high level of technology diffusion, social-esteem concerns might also emerge as thermal insulation has positive environmental spillovers (Bartiaux et al., 2016).

The agent's i decision rule is the following:

$$Adoption(i,t) = \begin{cases} 1, & if\ Z < [(1-\beta)/2]EB + \beta N \\ 0, & otherwise \end{cases} \tag{1}$$

where Z is a stochastic process that encompasses all the elements that affect adoption but are not explicitly included in the model. Z takes a uniformly distributed random value between 0 and 1. EB represents the direct net benefit that agent i acquires from adopting the technology derived from economic and behavioural motives (see the above-mentioned resource cost and intrinsic motivation in Eq. 2) and N is the importance of actor's i network of relationships in the choice to adopt (see Eq. (3)). Finally, we introduce β ($0 \le \beta \le 1$) to test the hypothesis that adoption depends on the different motives and that they might have a different relative weight. It follows that if $\beta = 0$, then N has

[5] Some authors suggest that the relationship between pro-environmental behaviour and environmental concern is not clear (Golob and Kronegger, 2019), while others relate environmental concern to an intrinsic motivation to protect the environment which makes individuals more likely to engage in pro-environmental decisions (Schleich et al., 2016). For a review see for example (Marcinkowski and Reid, 2019).

[6] The full explanation of the re-interpretation can be found in Chersoni et al. (2021).

no relevance and, vice versa, if $\beta = 1$ then economic and behavioural motives do not affect the agent's decision-making.

The agent's level of environmental concern is measured by v_i ($0 \leq v \leq 1$) and the financial burden of the investment is measured by c_i ($0 \leq c \leq 1$). The latter is the normalized ratio between the retrofit cost and the agent's perceived financial situation .[7] The relation between c_i and v_i is modelled as follows:

$$EB = (\upsilon_i - c_i) \tag{2}$$

Adoption is constrained by the perceived economic situation of the agent and is supported by the concern for the environment. If $EB = 0$, the net effect of economic and behavioural factors cancels out and the investment choice depends only on N. If, instead, the cost of the investment is too high relative to the actor's economic situation, the economic factor takes over the positive effects of the environmental driver ($EB < 0$). Finally, when $EB > 0$, the net benefit of acquiring the technology positively encourages the adoption process.

In the original model, social influence is a payoff modelled as the average expected reputational return from the action. In order to introduce the epidemic diffusion of innovation, we model social influence as a signal from neighbouring actors: as adoption takes off in the proximity of an actor, its probability of acquiring the technology increases. Moreover, to retain the heterogeneity of actors, and differently from Bénabou and Tirole (2011b), the neighborhoods are modelled as cliques in a small-world and preferential-attachment networks.

The role of social networks in the adoption of technologies is well known. Small-world networks (Watts and Strogatz, 1998) represent decentralised interaction (see for instance Beretta et al. (2018)). Conversely, preferential-attachment topologies (Barabási and Albert, 1999) imply centralised or hierarchical interaction that slows the information flows (Schilling and Phelps, 2005, 2007). We interpret the network as the medium on which imitation occurs. Imitation is guided by word of mouth transmission of information about the technology or by peer pressure (Young, 2009). The intensity of the imitative pressure will vary across the population depending both on individual variables (i.e. environmental concern) and on the position on the network (e.g. central vs. peripheral nodes).

We formalise social influence (N) as follows:

$$N = \frac{n_{adopt,i} {}^{*} q_i}{n_i} \tag{3}$$

where $n_{\mathrm{adopt,i}}$ is the number of neighbors of actor i who have already adopted the measure, q_i ($0 \leq q \leq 1$) is the actor's i imitation propensity (inversely proportional to v_i) and n_i is the agent's number of neighbors. Threshold models that account for personal network are more appropriate in the context where innovation is not directly observable and is perceived as uncertain and risky (Valente and Valente, 1996). Moreover, the inverse relation between q_i and v_i is well known within the behavioural economic literature (see for instance, Bénabou and Tirole (2011a)): when actors have low intrinsic motivations (i.e. low environmental concern) they are more sensitive to the influence of their peers (known as "conformity effect").

[7] Assuming that yi is the level of agent's economic satisfaction and $mi = 1/yi$ is the relative cost of the investment. $ci = (mi - mmin)/(mmax - mmin)$ is the normalized ratio between the cost of purchasing the technology and the agent economic status. Therefore, higher yi corresponds to lower mi and, consequently, to a lower ci. It follows that households with high economic status endure a low financial burden when acquiring the technology with ci that approximates 0.

3.2. The agent-based model

The model presented in section 3.1 is not analytically solved but simulated in an ABM to conduct a compositional understanding investigation.[8] Simulated time is discrete and the length of one-time step is not specified. The simulation stops when, given the value of the parameters, no further adoptions are possible.

The model is articulated in three typical components:

- the agent: the simulation has only one type of agent, the household. The household owns, as its features, the values of v_i, c_i, q_i: the environmental concern, the perceived economic situation, and the propensity to imitate, respectively. The population consists of 100 agents.
- the environment: a network in which each household is represented as a node and links are the connections among households. Links convey the information concerning how many agents have adopted in each household's neighbourhood. Neighbors are defined as households that are connected by, at least, one link. Links represent proximity on a social dimension: e.g. family, work or friendship connection. The model simulates two network structures: a small-world topology generated with the Kleinberg algorithm with high and low clustering (Kleinberg, 2000), and a preferential-attachment topology generated with the Barabasi-Albert algorithm (Barabási and Albert, 1999).
- the decision rule: each agent who can afford the technology decides whether to adopt by performing the following actions:
  - IF $\beta = 0$ THEN the household adopts when the difference between the level of environmental concern and the relative technology cost is > 0. Despite the simplicity of the formalisation, this covers a wide range of situations. For instance, when the household has a positive perception of its economic situation but also has a low environmental concern, adoption might not take place. Conversely, when the perceived economic situation is not entirely satisfactory, but the intrinsic motivation is high, adoption might occur.
  - IF $\beta = 1$ THEN the household will disregard economic and behavioural motives and will adopt, depending on its propensity to imitate, when at least one of its neighbors has adopted. When the propensity is low, a higher number of adopting neighbors is required to trigger the action, and vice versa.
  - IF $0 < \beta < 1$ THEN both economic and intrinsic motivations, and imitation concur to adoption.

β represents their relative weight.

At the simulation set up, we introduce a first adopter to trigger the imitative and adaptive behaviour (Rogers, 2010). Since the environment is separated from the agents and has its own topology, we can explore the effect of the position of the first adopter in the network by exploiting its centrality. Centrality measures the importance of a node in the network. We identify the first adopter as the household exhibiting the higher betweenness centrality. That is to say that such a household acts as a bridge between other nodes by lying on their shortest path. Thus, when simulating policy we have the adoption process started by an agent that has a high number of connections or that is connected to the most connected agents. Finally, as ABMs are stochastic models, each simulation run is repeated 100 times and the presented results are the average values (Wilenski and Rand, 2015).

4. Data

We exploit data from the *Second consumer market study on the*

[8] The software is available from: https://ccl.northwestern.edu/netlogo/. The code is available from the corresponding author.

functioning of the retail electricity markets for consumers in the EU (DG-Justice, 2016). The survey targets individuals aged from 18 to 95 who are fully or jointly in charge of paying the electricity bill in their household reporting information on behalf of the entire household. The survey collects information from about 30,000 households from 30 countries (EU28 plus Iceland and Norway) and covers a variety of topics. In addition to the usual socio-demographic information, it also includes information about the consumers' perceived ability to make rational and empowered choices concerning energy consumption and savings, their attitudes toward energy efficiency and renewable energy, and their adoption of energy-efficiency technologies.

From the dataset we extract information concerning 19,538 homeowners. That avoids split-incentives problems (Melvin, 2018; Castellazzi et al., 2017) and assures that the household has the contractual power to enact the investment decision (Bertoldi et al., 2021). In detail, we use the following data:

- Adoption of the technology. Survey question: Had your home (re-) insulated? Yes, No.

While the model is very general, our study focuses on the thermal insulation of the dwelling, (adoption level 38.37%). Our choice is due to two concurring considerations. First, while the ways renovation measures are implemented to improve thermal comfort might vary across climate conditions (e.g. combined with heating/cooling systems/ shading, green roofs), thermal insulation enables not only to reduce annual energy costs, but also to extend periods of comfort without relying on heating/cooling systems (Al-Homoud, 2004). Therefore, its diffusion is expected to exhibit a small variation across climatic regions so that we can ignore the geographic distribution. Second, thermal insulation implies a rather high-upfront cost and a considerable amount of technical and bureaucratic knowledge with respect to other energy-efficient technologies, such as LED bulbs and energy efficiency appliances (also available in the dataset). We believe it to be a good candidate for our study since adoption requires more active and articulated behaviour by the agents.

- Economic motives. *Survey question: Thinking about your household's financial situation, would you say that making ends meet every month is: Not easy at all, Not easy, Fairly easy, Very easy.*

The elicited qualitative information cannot be strictly interpreted as income. However, this does not represent a limitation of our study because investments do not rely solely on income but also on wealth or credit constraints. Moreover, since our data regards countries that are characterized by different socio-economic conditions and cost of living, households income information might not be comparable. In particular, as the concept of welfare cannot be reduced only to a single criterion based on income, an alternative consists of relying on subjective perceptions of financial difficulties (Deaton, 2010). The perceived financial situation can affect not only future behaviour (Bertrand et al., 2004), but also the objective situation of income poverty (Ayllón and Fusco, 2017). Such subjective perceptions are also context-dependent (Genicot and Ray, 2017), as they exhibit reference-dependence (i.e. individuals in rich countries might feel they have unmet aspirations due to a higher reference point determined by social comparison (Castilla, 2010)).

- Intrinsic motivation/environmental concern: Survey question. It is important for me to save energy for environmental reasons: Totally disagree (0) - Totally agree (10).

The elicited question reflects the intensity of homeowners' intrinsic motivation to invest in energy efficiency due to environmental reasons, i.e. their level of environmental concern. Households can minimise adverse environmental effects related to their energy consumption by increasing the energy efficiency of their dwelling. Therefore, the individual motivation in protecting the environment is associated with the level of environmental protection achieved through the investment.

Fig. 1 shows the distribution of economic and behavioural factors.

The income distribution is almost symmetric and concentrated around its medium values, while envi-ronmental concern distribution is left-skewed, with more than 55% of homeowners reporting a high level (8-totally agree) of environmental concern. We cannot rule out the possibility for social desirability to play a role in this, as discussed in Section 7.

We perform a chi-squared test of independence to assess whether the selected economic and behavioural factors are a good predictor for thermal insulation investments. Results show that the variables are statistically dependent (see Appendix A). Fig. 2 shows a positive association between thermal insulation investment, high level of environmental concern (i.e., 8 - Totally agree) and very satisfactory financial situation (i.e., "Very Easy"). Conversely, the investment decision is negatively associated with perceived financial difficulties (i.e., "Not Easy at All").

Data are mapped into a population of 100 agents. The transformation does not affect the adoption process, due to network fractal properties (Wasserman and Faust, 1994; Chen et al., 2012). We normalise the variables distributions (see Fig. 1) and translate them into the parameters y_i and v_i for the simulated agents. In the model, homeowners' financial situation is used to compute the relative investment cost (c_i in Eq. (2)), while v_i accounts for the behavioural factors affecting the investment decision. The model assumes that the households with $y_i = 0.1$ and $c_i = 1$ (i.e., "Not Easy at All") do not have the economic resources to afford the investment. Vulnerable households have less access to internal capital and therefore suffer more from the economic and financial barriers to energy efficiency (Ugarte et al., 2016). Thus, in the absence of financial incentives, homeowners with $c_i = 1$ are not able to adopt thermal insulation technology.

5. Main findings

In this section, we first illustrate the behaviour of the ABM and, then, we simulate the effect of diverse policy interventions. Policies are chosen according to the general prescriptions deriving from the streams of literature we are taking into account:

- Drawing on economic-financial literature, we implement an improvement in the households' economic situation. This can be thought of as a subsidy, tax credit or deduction, rebates or loan subsidy (Economidou et al., 2019, 2021). By exploiting the possibility of investigating differentiated policy effects across a sub-sample of the population, we consider interventions that operate on the population and on the most disadvantaged households.
- Drawing on behavioural literature, we simulate an intervention (e.g. a pro-environmental campaign) that targets intrinsic motivations by emphasising the environmental cause.
- Drawing on literature in technology diffusion, we observe the effect of different network topologies on the adoption rate and we implement interventions that target the most central households. These interventions can be thought of as making trusted and visible members of the community act as a testimonial for the technology and foster its diffusion.

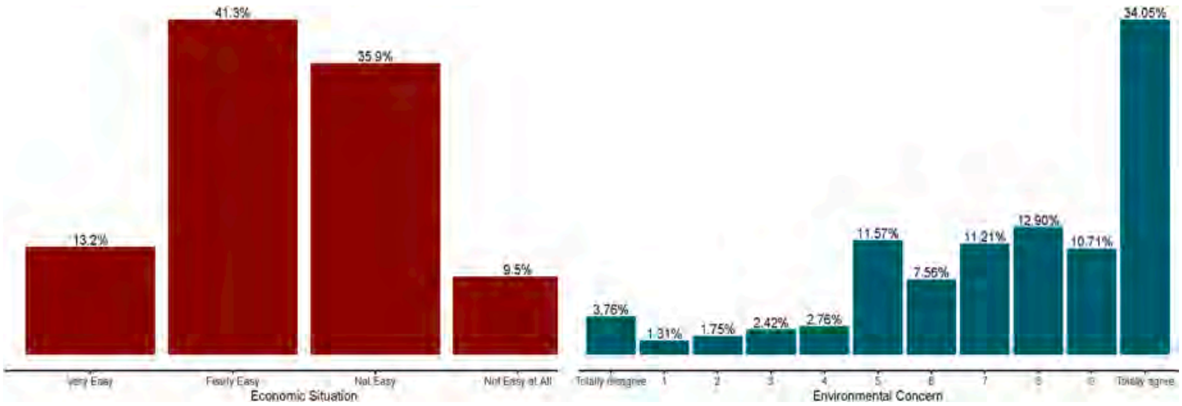


Fig. 1. Relative frequency distributions of homeowners' perceived financial situation and level of environmental concern. Sample size 19,538. Source: Authors' calculation.

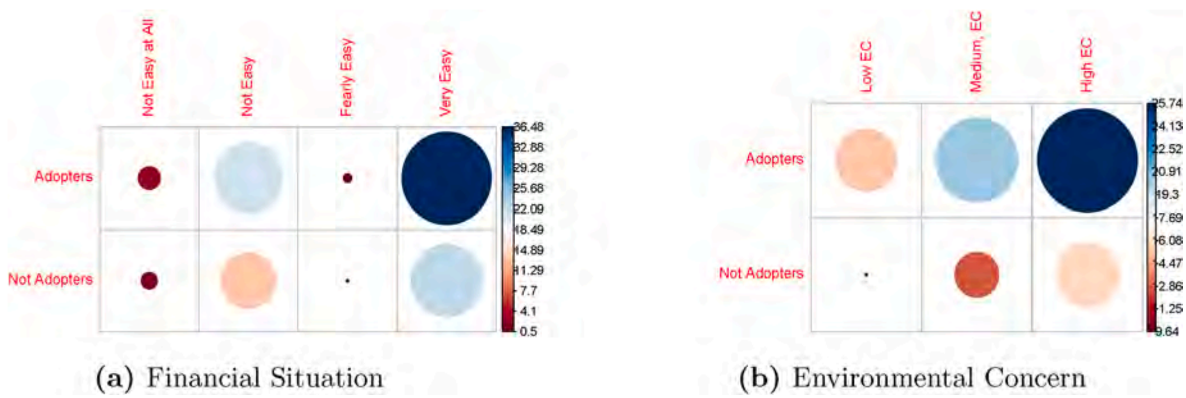


Fig. 2. Correlation plots of the chi-squared test standardized residual. Fig. 2a shows the correlation matrix between the homeowners' perceived financial situation and the thermal insulation adoption. Fig. 2b shows that correlation matrix between the homeowners' levels of environmental concern and thermal insulation adoption. The size of the circles represents the cell contribution to the chi-square. The colours of the circles give information on the type of association between the variables: positive residuals are in blue, negative residuals are in red. Source: Authors' calculation. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

5.1. Model behaviour

The general behaviour of the model has been explored in Chersoni et al. (2021). Here we briefly recall the main findings. The model shows that the role of the network is not linearly increasing with the value of β, and the imitation effect (i.e., N) prevails only for high values of β, with a more marked effect in preferential-attachment network (for the complete results of the sensitivity analysis of the parameter β see Fig. 6 in Appendix B). Interestingly, when economic and behavioural motives matter, results challenge the finding that adoption is lower and slower in preferential attachment networks. This is due to the effect of central nodes on the population characterized by a lower intrinsic motivation. This suggests that making the action of adoption more visible might effectively increase individual motivation to adopt by strengthening peer effects.

For what concerns the model informed with data, we map the distribution of the observed parameters (i.e. c_i and v_i) into a population of 100 agents and observe that the data-fed model is consistent with the theoretical model as illustrated above. That is, the classical S-shaped curve of the epidemic models, where only imitation matters, is well reproduced for $\beta = 1$ (Fig. 3b). When agents behave in isolation instead, time is not relevant for adoption and the households that satisfy the economic and behavioural conditions adopt simultaneously (Fig. 3a) . This shows that the model can be fed with data and retain its theoretical results. This encourages its use as a base for simulating policy.

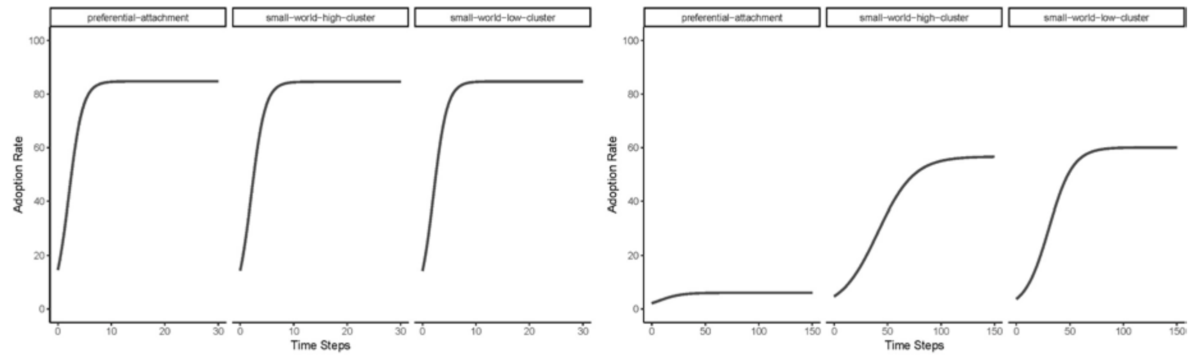
From the simulations of the model in the absence of policies, we can draw preliminary information on the relative importance of the theoretical elements and on the policy that can be implemented. Comparing the sets of simulation to the empirical observation shows that neglecting the imitative drive ($\beta = 0$) leads to an overestimation of the adoption rate, while neglecting the behavioural motive and economic characteristics ($\beta = 1$) produces its underestimation [9].

5.2. Policy simulations

We exploit agent-based modelling to analyse policy-making in both a prospective and a retrospective manner.[10] Prospective models simulate the effects of policy design. Since ABMs rely on nonlinear out-of- equilibrium theory, they can help identify critical thresholds: small changes of magnitude in an intervention might result in radical and irreversible changes in the system of interest. Moreover, in our study, multiple systems are involved – the household features and the environment in which they interact. Therefore, ABMs can map the trade-offs or synergies of policies in those systems and uncover their unintended or unexpected consequences. Retrospective models can identify the reason why policies have or have not played out the way they were expected to. This is especially relevant when data is not available: in our case, the network of household connections is not observed, yet it can be included

[9] On average, when $\beta = 0$ the simulated adoption rate is 47% higher then the observed one (i.e. 38.37%), while, when $\beta = 1$, the simulated results is lower than the observed one and the difference depend on the underlying network structure.

[10] This classification is proposed and discussed at length by Hammond (2015) and Fontana and Guerzoni (2022) (ming).



(a) $\beta = 0$ (b) $\beta = 1$

Fig. 3. Fig. 3a shows the adoption curve for $\beta = 0$ by network topologies. Fig. 3b shows the adoption curve for $\beta = 1$ by network topologies. The x axis represents the discrete simulated time; the length of one-time step is not specified. The y axis represents the average adoption rate observed after 100 simulations run. Source: Authors' calculation.

in the analysis. Finally, since ABMs retain the heterogeneity of the population, it can also highlight the differentiated effect of intervening in sub-samples of the population.

5.2.1. *Financial incentives*

The up-front cost associated with energy renovation investments can be reduced through subsidies, tax credits, tax deductions, rebates or loan subsidies (Gillingham et al., 2009; Bertoldi et al., 2020; Economidou et al., 2019, 2021). In particular, financial incentives specifically targeting low-income households are able to deliver multiple benefits of energy efficiency, creating conditions that support occupant health, well-being, living comfort, and disposable income (Ugarte et al., 2016).

Some EU Member States already engage in such differentiated interventions. For instance, The Sus-tainable Energy Authority of Ireland launched two initiatives: the *Better Energy Homes* ,[11] which funds 30% of the total investment cost of heating and insulation measures, and the *Better Energy Warmer Homes Scheme* ,[12] which specifically targets low-income homeowners offering free home energy upgrades. Similarly, the *Warmer Homes Scotland* [13] programme in the UK focuses on heating and insulation measures offering specific funding opportunities also to tenants experiencing fuel poverty.

We simulate a generic decrease in the investment cost of the households that reduces the value of the parameter c_i to investigate how adoption reacts to changes in the rebate and the targeted population.

5.2.2. *Behavioural interventions*

To promote pro-environmental behaviours, such as investing in energy-efficiency measures, many campaigns emphasise financial benefits (Evans et al., 2013). However, campaigners have recently raised the issue that only tapping into financial motives may actually fail to promote the desired effect (Thøgersen and Crompton, 2009). Conversely, programmes that target intrinsic motivations might increase the likelihood to engage in pro-environmental behaviours, which has been shown to be significant at least for pro-environmental intentions (Maki et al., 2019). For example, to leverage intrinsic motivations, campaigners can make salient that one way to decrease GHG emissions is engaging in a costly action, like investing in costly energy efficiency measures (Carrico et al., 2018).

We simulate a pro-environmental campaign (Hungerford and Volk, 1990; Maki et al., 2019) that fosters the population's environmental concern. To appreciate the effect of this intervention, we increment the value of the parameter v_i for an increasing share of the population.

5.2.3. *Social environment interventions*

Empirical and experimental evidence (Valente, 2012; Allcott, 2011; Bicchieri, 2005) shows that households' choices are affected also by their social environment. The social *milieu* acts as a medium in which information circulates via word of mouth communication, and in which observation and, possibly, imitation of others' behaviour play a crucial role. The design of such policy tools involves several aspects. First, the context in which information is provided matters. Individuals might not rely on the information provided by authorities or organizations they might not trust (Palmer et al., 2013). Moreover, individuals have different levels of environmental concern, of income etc., and different roles within their social context, therefore influencing their surroundings in a variety of ways. As an example, empirical evidence suggests that trusted messengers can contribute to creating a shared norm in the community and promote positive behaviours, such as pro-environmental ones (Moseley and Stoker, 2013; Bicchieri and Dimant, 2019; Scott et al., 2016). In addition, identifying 'trusted messengers' can help reinforce the effect of other policy interventions such as financial ones. For instance, a survey conducted by the Sustainable Energy Authority of Ireland highlights the role of a trusted source as key to improving the attractiveness of subsidies and the support programme for energy efficiency in the residential sector. [14]

We account for the effect of trust and heterogeneity of roles by simulating a targeted norm-based inter-vention that encourages adoption through the role of central members of the community (Scott et al., 2016; Bicchieri and Dimant, 2019). Information is spread across the network by the households that have more connections in the social structures – i.e. the network nodes that have the highest betweenness centrality – and therefore can be considered trusted members by the community. To simulate the effect of such an intervention, we consider the most central households as first adopters.

The simulation explores the effect of the policy on two coexisting levels of social interactions. On the one hand, preferential-attachment reproduces interaction that is typical of the media, where politicians, influencers, and scholars can step forward in promoting environmental issues. On the other one, the small-world architecture mimics

[11] https://www.seai.ie/publications/Homeowner-Application-Guide.pdf.
[12] https://www.citizensinformation.ie/en/housing/housing_grants_and_schemes/warmer_homes_scheme.html.
[13] https://www.gov.scot/policies/home-energy-and-fuel-poverty/energy-saving-home-improvements/.
[14] https://www.seai.ie/publications/Behavioural-insights-on-energy-efficiency-in-the-residential-sector.

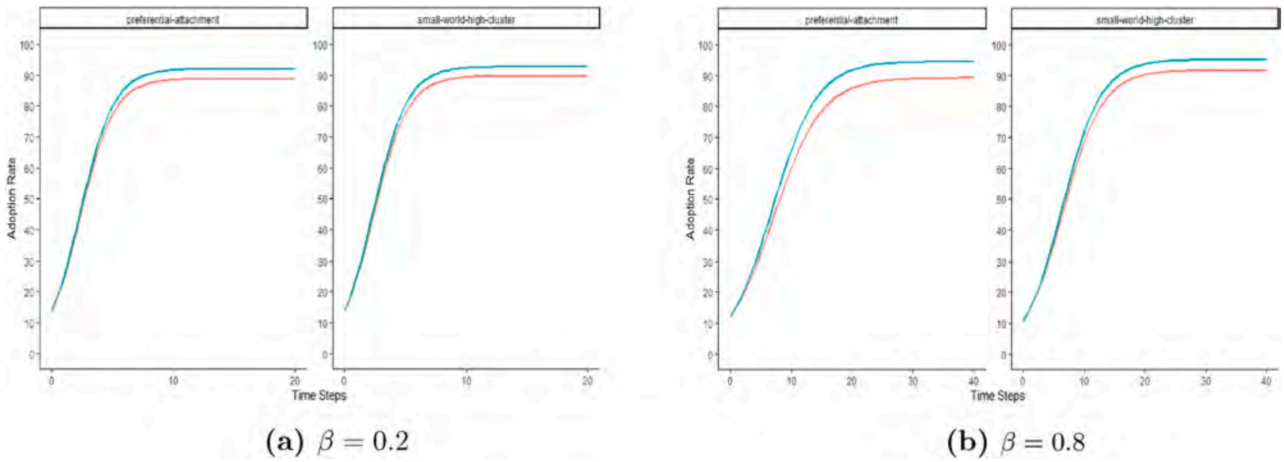


Fig. 4. The figure shows the results of financial interventions (Not targeted and Targeted) for low and high values of β under the simulated network topologies. The figures average the intervention intensity and the share of the population. The red line is the adoption curve under non-targeted financial incentives, while the blue line represents the adoption curve under the targeted financial intervention. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

interactions that take place in everyday life, when households communicate with their neighbors. The differences between the two allows us to specify better the targets for programmes that aim at identifying "trusted individuals" by contextualising their interaction. Moreover, they allow appreciating how the speed of diffusion of the information varies in relation to the network topology.

5.3. Policy simulation results

Far from being prescriptive, the results expounded in this section aim at showing that conceiving policies that lean on a broader framework can lead to a more thorough understanding of the adoption process and, consequently, to more effective policy interventions. In what follows, we describe how policy outcomes change when we follow the proposed threefold theoretical approach. We are aware that this information is merely indicative. Nevertheless, we are convinced that, in spite of the many limitations, these results constitute a useful base for making the case for a more encompassing theoretical scaffolding for policy design, as we will discuss in the following section. In what follows we discuss the results of the diverse policy interventions and compare their effectiveness (the policy simulation results are reported in Appendix C, see Figs. 7-17).

5.3.1. Financial incentives

We articulate financial incentives as a cost reduction in the form of a rebate in three settings: rebate amounting to 10%, 50%, 100% of the investment cost granted to the 10%, 50%, 100% of the population and we explore its effect on the adoption curve as the weight of the social influence (β) in the form of imitation varies. Moreover, we consider an intervention that targets households that perceive themselves in a difficult economic situation versus a watering-can financial intervention.

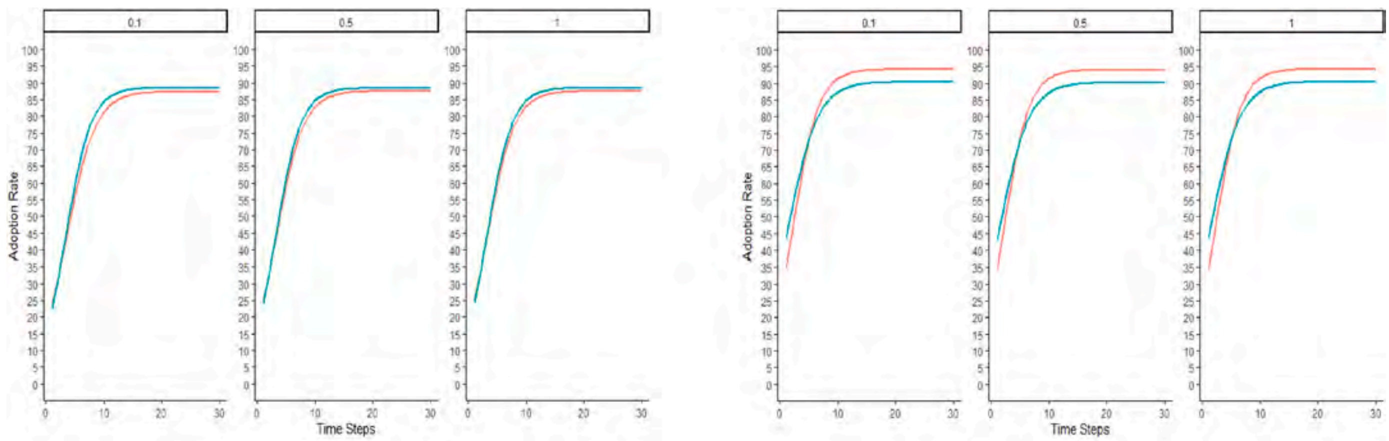
When social influence is not simulated ($\beta = 0$), only economic and intrinsic motivation matter. By construction, when the rebate covers the entire investment cost, the household with low environmental concern will not adopt. On the other hand, when only social influence matters ($\beta = 1$), adoption is only driven by the behaviour of the other households and, therefore, financial incentives are ineffective and only the topology of the network affects the adoption rate, with preferential-attachments networks less favourable to diffusion with respect to small-world topologies. Finally, when all three drivers play a role ($0 < \beta < 1$), the adoption process shows interesting results. Even when small, the imitation effect triggers the adoption of households with a low intrinsic motivation. The effect is higher for lower values of β: as the parameter value increases, the effect of a low intrinsic motivation loses power, and the imitation effect prevails ($ec = 0$ then $q = 1$). However, as the value of β increases, the imitation effect is counterbalanced by the intrinsic motivation: a high intrinsic motivation results in a negative imitation propensity that negatively affects the adoption rate ($ec = 1$ then $q = 0$). That is particularly true in small-world networks, where information travels smoothly due to a higher connections between nodes, and a negative imitation propensity highly affects adoption (see Fig. 4). In preferential-attachment structures, where the hierarchical network structure reduces the probability of having adopting neighbors, this effect is nuanced particularly when watering-can financial interventions are considered.

Overall, the targeted intervention is always more effective than the watering-can financial measure. The difference between the interventions resides in the features of the households in a difficult economic situation as represented in the data: they have rather similar rates of environmental concern and the negative imitation effect hits them all, but when households are not filtered according to a criterion, the imitation effect gains less traction. It is worth noting that this effect is observable only because we are using an agent-based simulation and considering more than one decision driver.

5.3.2. Behavioural interventions

We model the behavioural interventions as a pro-environmental campaign that increases the environmental concern of 10%, 50% and 100% for and increasing share of the population (10%, 50%, 100%) and we observe its effect on the adoption curve as the weight of social influence (β) in the form of imitation.

By construction a higher level of environmental concern has two effects: first, it reduces the gap between v_i and c_i, thus making adoption



(a) Pro-environmental Campaign (b) Norm-based Intervention

Fig. 5. The figure shows the results of the Pro-Environmental Campaign and the Norm-based Intervention for $\beta = 0.5$. The figures compare the intervention intensity (0.1, 0.5, and 1 increases in the level of environmental concern) by network type. The red line is the adoption curve under the preferential-attachment network and the blue line is the adoption curve under the small-world structure.
(a) Pro-environmental Campaign **(b)** Norm-based Intervention. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

more likely; second, it makes individuals less sensitive to the behaviour of others, making imitation harder. We observe that the latter effect is neutralised in preferential-attachment topology. Interestingly, when only economic and behavioural motives drive the adoption ($\beta = 0$), the increasing level of intrinsic motivation of the entire population has a negligible effect on the adoption level. This is caused by the budget constraint of the households that experience a difficult economic situation and the unresponsiveness of those who already have a higher level of environmental concern. This result suggests that behavioural motives are less powerful than the economic ones in driving the adoption process; thus, a 100% rebate is different from an increase of environmental concern of 100% for the whole population.

5.3.3. *Social influence interventions*

Modelled as a targeted-norm-based intervention where the most central nodes in the social network – the most trusted members of the community– are the first adopters. Yet again, the intervention is simulated for an increasing share of focal nodes (10%, 50%). With respect to the pro-environmental campaign, this intervention targets households that act as bridges between different parts of the network and can be thought of as influencers.

For the extreme values of β, the model behaves as in the baseline version: when $\beta = 0$ households that have no financial resources cannot adopt, while when $\beta = 1$, adoption is triggered only by the imitative response. In the latter case, the effect of the social influence intervention is maximum because the first adopters are the households that cover the most influential positions in the social network and, consequently, spread the imitation in many clusters (see Fig. 17 in Appendix C). That happens particularly in the preferential-attachment topology, since the hierarchical structure spreads imitation also in clusters that are not linked. In small-world networks, the effect of the most influential households is less important because information travels locally through clusters. This result is rather an interesting complement to the behavioural economic theory that suggests targeting the most trusted members of a community to create a shared norm in the community. We show that the net effect of such an intervention is mediated by the structure of interaction.

The fostering effect on the adoption is also observed for lower values of β with a reduction of magnitude (see Fig. 5). A similar effect is observed in the pro-environmental campaign, where a positive effect on adoption is obtained from small increments of environmental concern (see Fig. 5a). However, the norm-based intervention proves to be more effective.

The different effects of the networks that emerge from the policy interventions partially depend on the fact that the pro-environmental campaign targets the level of environmental concern, which has an effect on the imitative behaviour of the households. At the same time, financial incentives reduce the investment costs with no effect on the behaviour of the other households. That casts doubts on the exhaustiveness of models that consider only social effects as drivers of individual choice to adopt.

6. Discussion and policy implications

The paper is, to the best of our knowledge, the first attempt at expanding the policy approach to the adoption of energy-efficient technologies by merging the existing literature. We envisage an agent whose motives for action are manifold and possibly divergent. Our hypothesis is that decision-making is not only determined by economic factors but also by intrinsic motivations and social influence, and we suggest that policymakers could profitably exploit them to increase the effectiveness of policies. We use data to retain the heterogeneity of the population, which is a common trait in social computational science, and to see how policy will play out when the three general motives behind adoption are accounted for. Results show the relevance of our approach, since policies that leverage only one motive are nonetheless affected by the others. For example, providing financial incentives will not be completely effective if the households are not environmental concerned and/or do not have access to reliable information. Simulations show intervening on the economic, behavioural or social motives results in different policy outcomes and implies different levels of public expenditure.

However, this evidence cannot be taken as prescriptive, mainly due to the limitations in the availability of data. Firstly, there is no record of the networks that connect the households in a social system. The diffusion of computational social science (Lazer et al., 2009), also within the European Union policy agenda, opens up a new conception of data that includes information drawn from social media platforms and that, in the future, could be exploited for policy purposes (Fontana and Guerzoni, 2022). Secondly, we have no data on the relative importance of the economic, intrinsic and social motives. As the paradigm of the *homo oeconomicus* is progressively left behind, the idea of heterogeneity of decision-makers is gaining traction. The survey we have exploited to parametrise the simulation constitutes a fitting example of how behavioural factors such as environmental concerns are increasingly gaining importance for policymakers. Moreover, our results suggest that a further step is necessary: information on motives should be gathered in ways that allow expressing their relative weight within the agent's decision process in order to have a covering description of the policy recipients. Thirdly, our model relies on self-reported data that might suffer from the intention-action gap (Alemanno and Sibony, 2015; Marcinkowski and Reid, 2019; Carson and Groves, 2007).[15] However, it is worth noting that, since we are not engaging in an econometric exercise, we do not face the same issue. Our variables are not predictors but initial parameters that reflects heterogeneity.

Keeping these limitations in mind, we can still discuss general policy implications that descend from our main hypothesis. Simulations show that a financial intervention that targets households in difficult economic situation increases adoption more than the watering-can financial intervention. This results descend directly from the combination of two ideas that are shared and discussed in the literature (Schleich, 2019) but seldom operationalized: if the environmental concern is low, the financial incentive to invest in energy efficient technology is not effective in spite of the economic situation; whereas removing the budget constraint for households that face a difficult economic situation has a stronger effect in spite of the environmental concern. Indeed, the magnitude of the difference cannot be taken as an empirical indication, but the results remain an interesting hint both to devise future policy and to understand why past interventions have missed their targets. Regarding behavioural policy, we observe that pro-environmental campaigns suffer from severe limitations in promoting adoption especially within those who are already intrinsically motivated (see for instance Dütschke et al. (2018)). For what concerns norm-based interventions, the huge difference in performance between centralised (preferential-attachment topology) and decentralised (small-world topology) interactions suggests that, in the latter case, large-scale collective adoption through a norm-based intervention should be preceded by actions that help connect different groups (clusters) and develop a broader collective identity (Hornung et al., 2019).

While we have simulated interventions separately, further research should investigate the idea that be-haviourally informed interventions could be used in combination with traditional ones (Ewert, 2020): how and what combinations of traditional, behaviourally and socially informed instruments are effective at pro-moting renovation decisions. One way to assess such efficacy would be by scrutinising the behavioural mechanisms (e.g. behavioural spillovers, synergic effects (Drews et al., 2020)) on which such a combination operates.[16]

7. Conclusions

A puzzle of central relevance to energy policy is why there are still untapped opportunities to reduce energy demand and CO_2 emissions through the increase of energy-efficiency investments. The empirical evidence reports a gap between the optimal level of adoption and the one that is actually undertaken by households, the *energy efficiency gap* (Hirst and Brown, 1990; Jaffe and Stavins, 1994). The issue is particular evident when the renovation of buildings is considered. Despite the increased policy interventions in Europe, the renovation rate is still well below the expected level (Rosenow et al., 2017).

The economic literature has extensively investigated the factors underlying such under-investment con-cluding that market failures prevent investing in energy-efficient technologies (Gillingham et al., 2009;

Bertoldi, 2020). Behavioural economics gives the issue a broader perspective that includes individuals' heterogeneity, and stresses non-egoistic and non-strictly economic motivations (Allcott and Greenstone, 2012; Schleich et al., 2016; Fischbacher et al., 2015). We introduce a further explanation that calls in the social structure on which interaction unfolds. It is largely acknowledged that social influence reinforces the adoption of technologies through imitation (Rogers, 2010).

This study applies an ABM to study households' decision to thermally insulate their dwelling. The model attempts at encompassing the financial, behavioural, and social perspectives (Chersoni et al., 2021) on adoption in order to offer a tentative covering framework to simulate the effect of various policies, namely information programs, norm-based interventions and financial incentives. The model is calibrated according to the information contained on a dataset of European households from which we extract economic and behavioural information.

In spite of the many limitations, results confirm that when economic, behavioural and social motives are accounted for, then policy interventions might produce unexpected and even counterintuitive outcomes. Results also suggest that the road taken is worth pursuing by perfecting this type of modelling and possi-bly, through the advancement of computational social science, by collecting more qualitative data on the households decision-making process.

CRediT authorship contribution statement

Giulia Chersoni: Conceptualization, Methodology, Formal analysis, interpretation of data, Writing – original draft, Writing – review & editing, Approval of the version of the manuscript to be published. **Nives DellaValle:** Conceptualization, Methodology, Formal analysis, interpretation of data, Writing – original draft, Writing – review & editing, Approval of the version of the manuscript to be published. **Magda Fontana:** Conceptualization, Methodology, Formal analysis, interpretation of data, Writing – original draft, Writing – review & editing, Approval of the version of the manuscript to be published.

[15] However, the use of surveys is common practice in economics to understand the 'how and why' behind individual behaviour when no other desirable measure is available (Sovacool et al., 2018). As an example, in environmental economics, the contingent-valuation survey is extensively employed to elicit individual willingness to pay (WTP) for preserving environmental resources (Boulier and Goldfarb, 1998). Large-scale surveys can also be used to predict behaviour when they embed validated items in the laboratory. As an example, Falk et al. (2016) recently advanced a preference module able to capture key economic preferences (time and risk preferences, altruism, reciprocity, and trust) that are significant predictors of behaviour in incentivized experiments.

[16] To this end, the experimental approach, rather than agent-based modelling, would be a better suited methodology (Lunn, 2018; Falk and Heckman, 2009).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendices.

A Correlation Analysis

The Chi-Squared test of independence is used to analyse if an association between thermal insulation adoption and homeowners' financial situation, and level of environmental concern exists.

Chi-Squared test of independence: thermal insulation - financial situation.

Pearson's Chi-squared test

data: tb2.ho.

X-squared = 54.367, df = 3, p-value = 9.37e-12.

Chi-Squared test of independence: thermal insulation - environmental concern.

Pearson's Chi-squared test

data: tb3.ho.

X-squared = 148.23, df = 2, p-value < 2.2e-16.

Both test results in a $p - value < 0.05$ indicating that the two variables are not statistically independent. In order to study if the association between the variables is positive or negative, we plotted the Chi-squared test standardized residuals (see Fig. 2).

B Sensitivity Analysis β

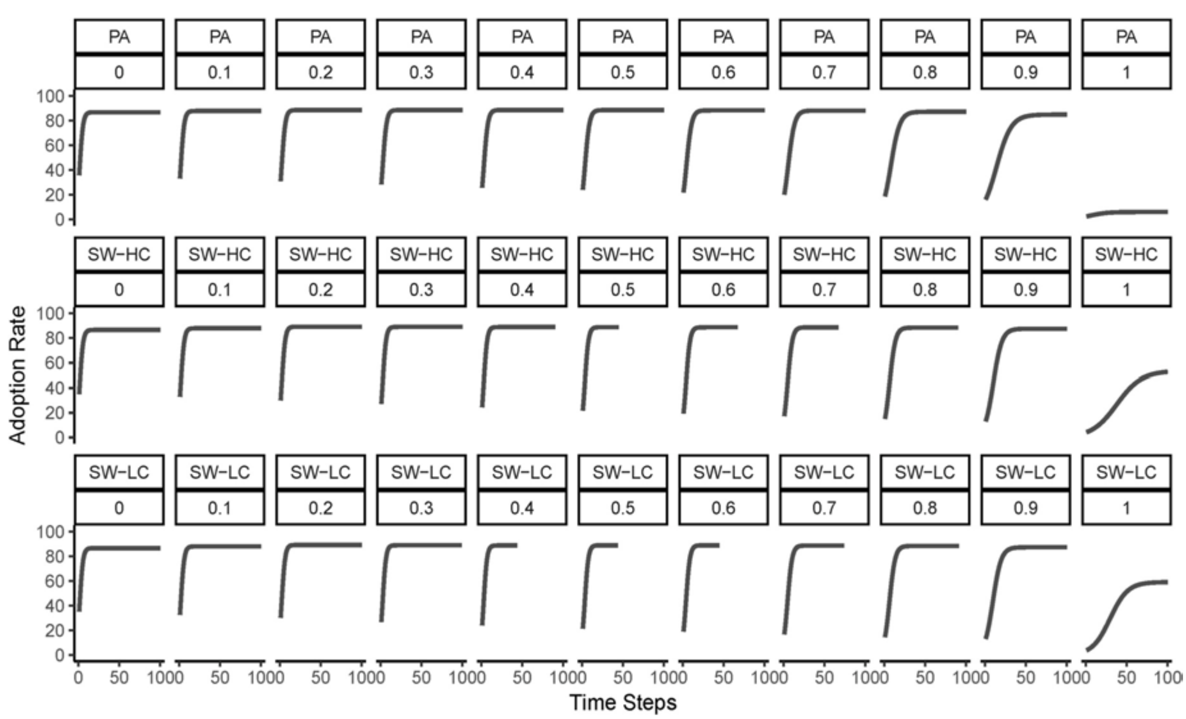

Fig. 6. Sensitivity analysis of β per type of network. Type of networks: PA preferential-attachment; SM-HC small-world high-cluster; SM-LC small-world low-cluster. Source: Authors' calculation..

C. Results Policy Simulation

In what follows we analyse the effect of β on the policies outcomes.

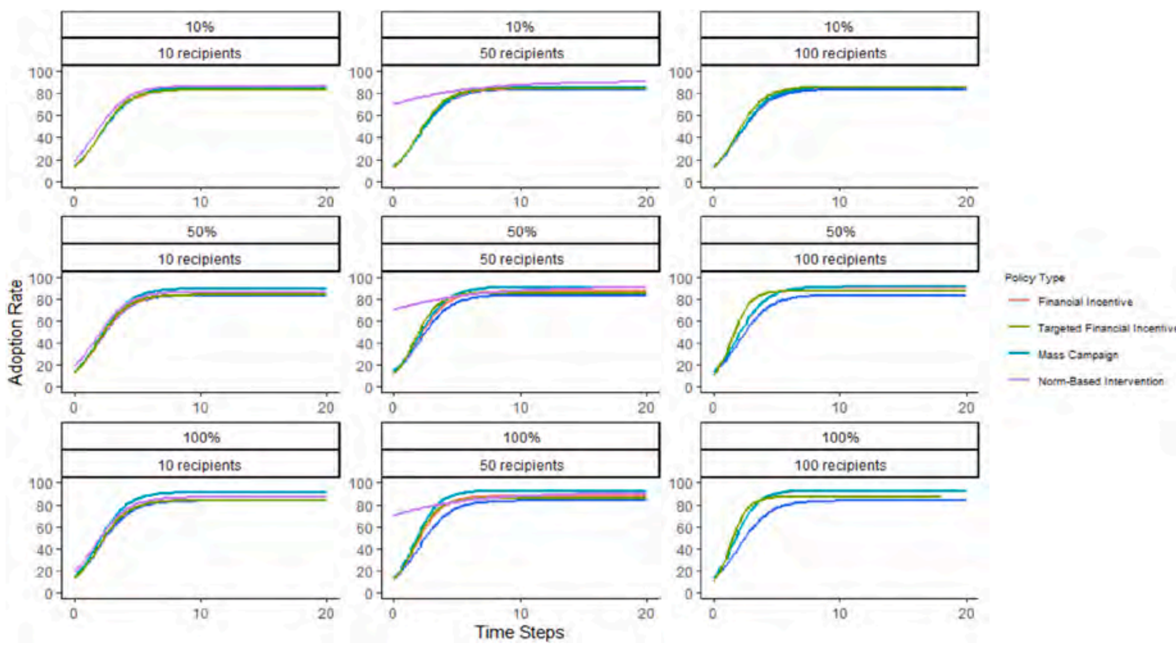

Fig. 7. Policy simulation results for $\beta = 0$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

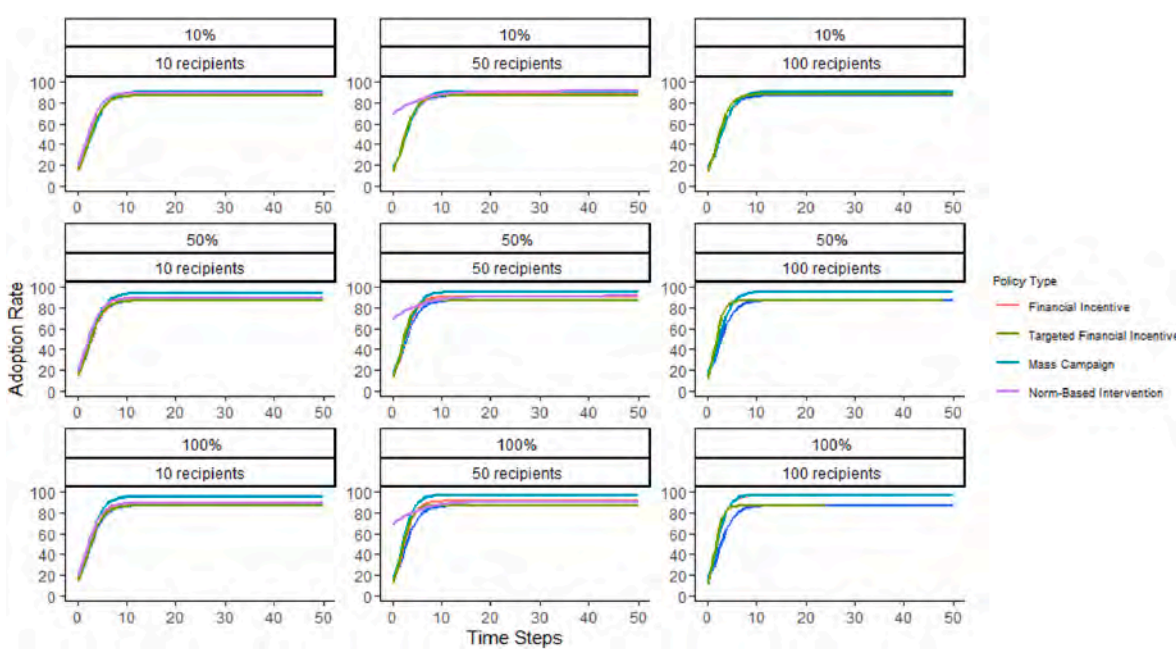

Fig. 8. Policy simulation results for $\beta = 0.1$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

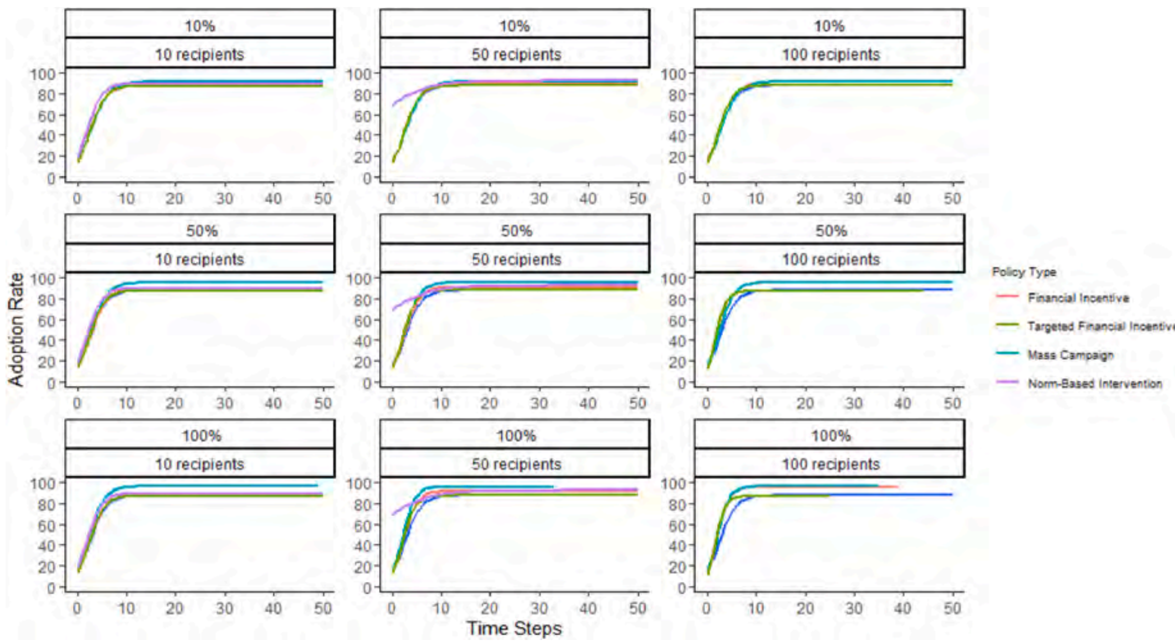

Fig. 9. Policy simulation results for $\beta = 0.2$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

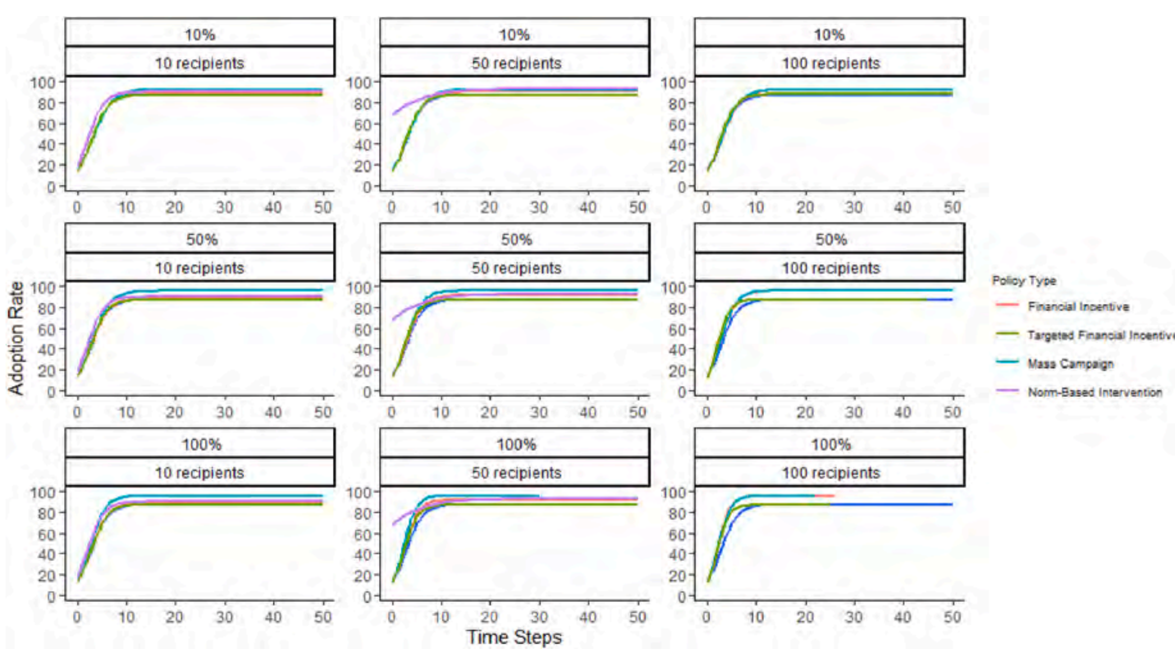

Fig. 10. Policy simulation results for $\beta = 0.3$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

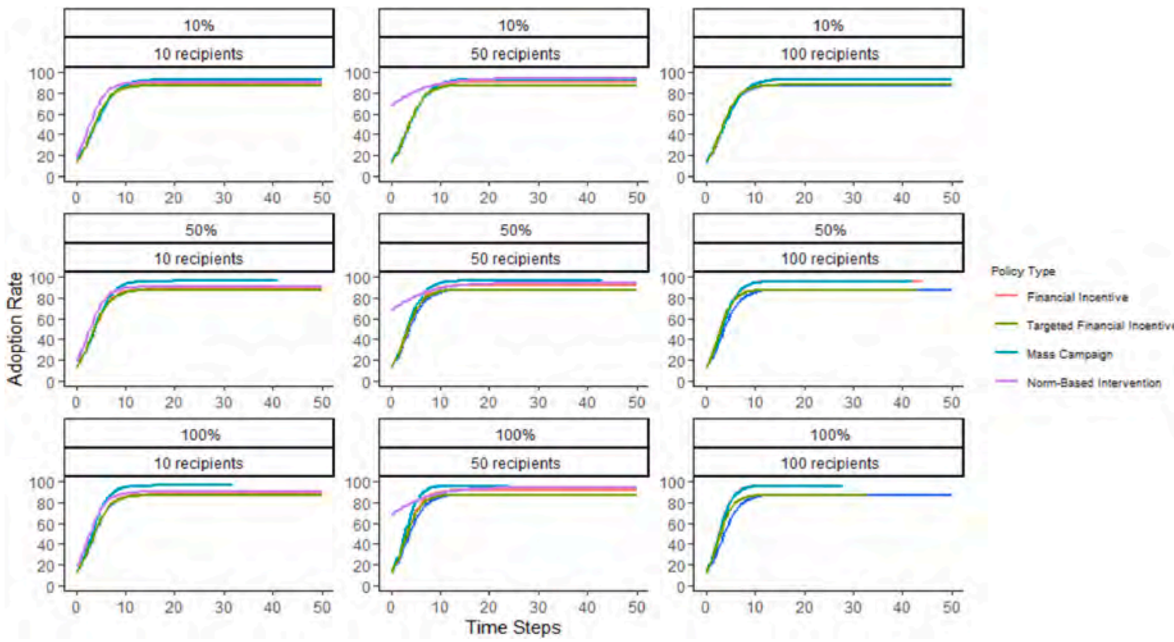

Fig. 11. Policy simulation results for $\beta = 0.4$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

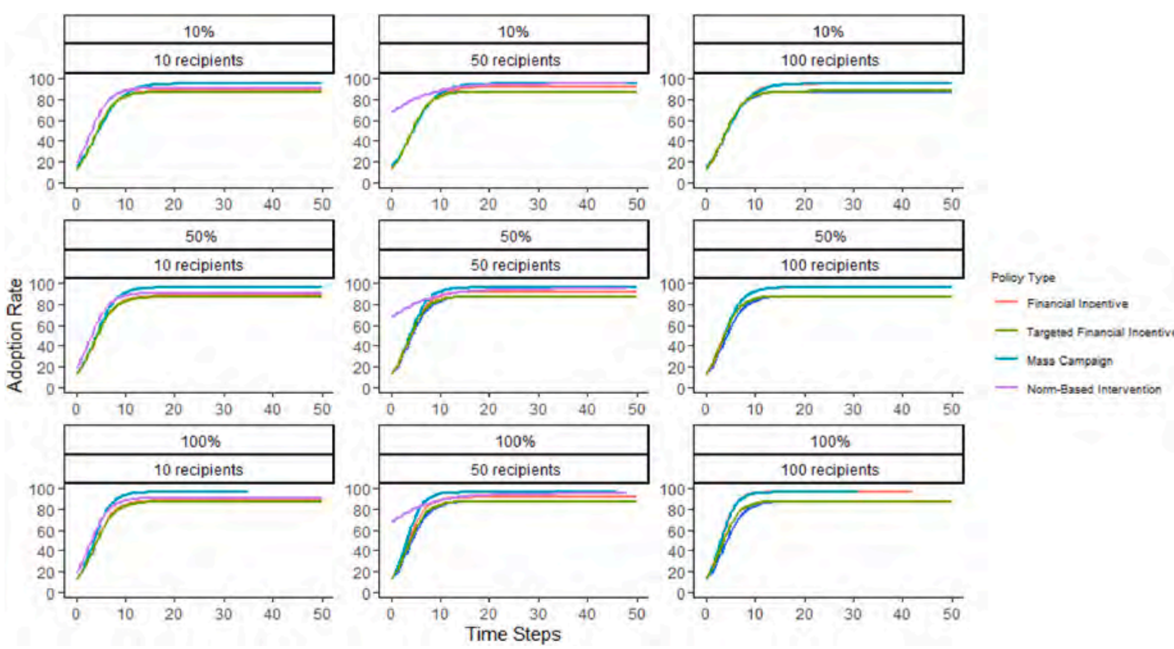

Fig. 12. Policy simulation results for $\beta = 0.5$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

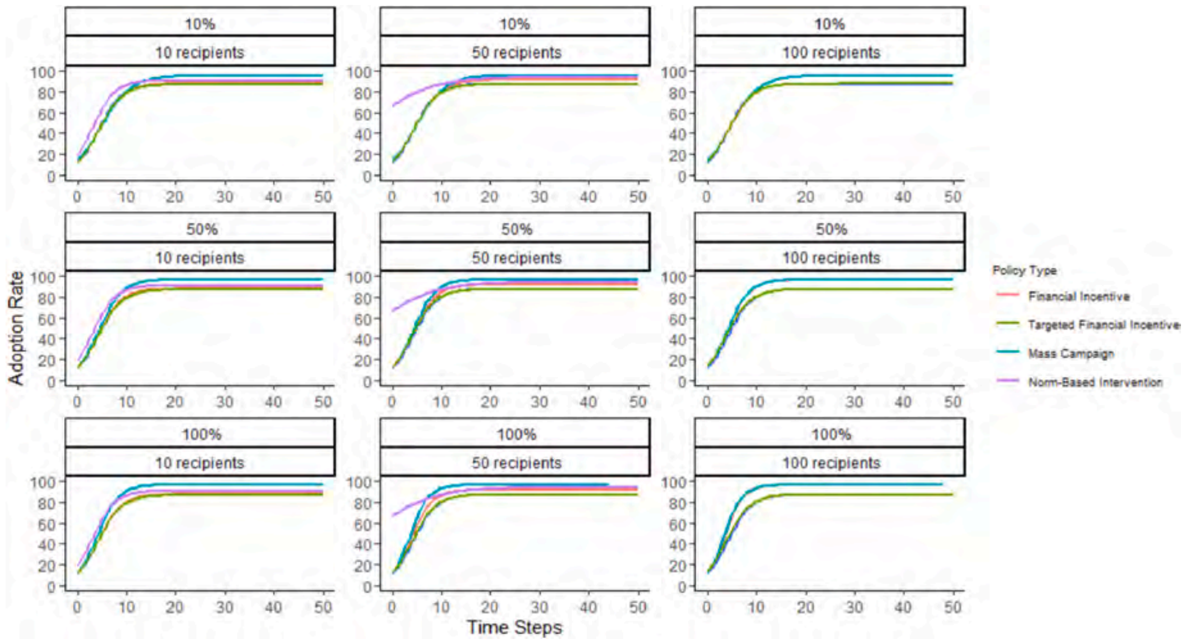

Fig. 13. Policy simulation results for $\beta = 0.6$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

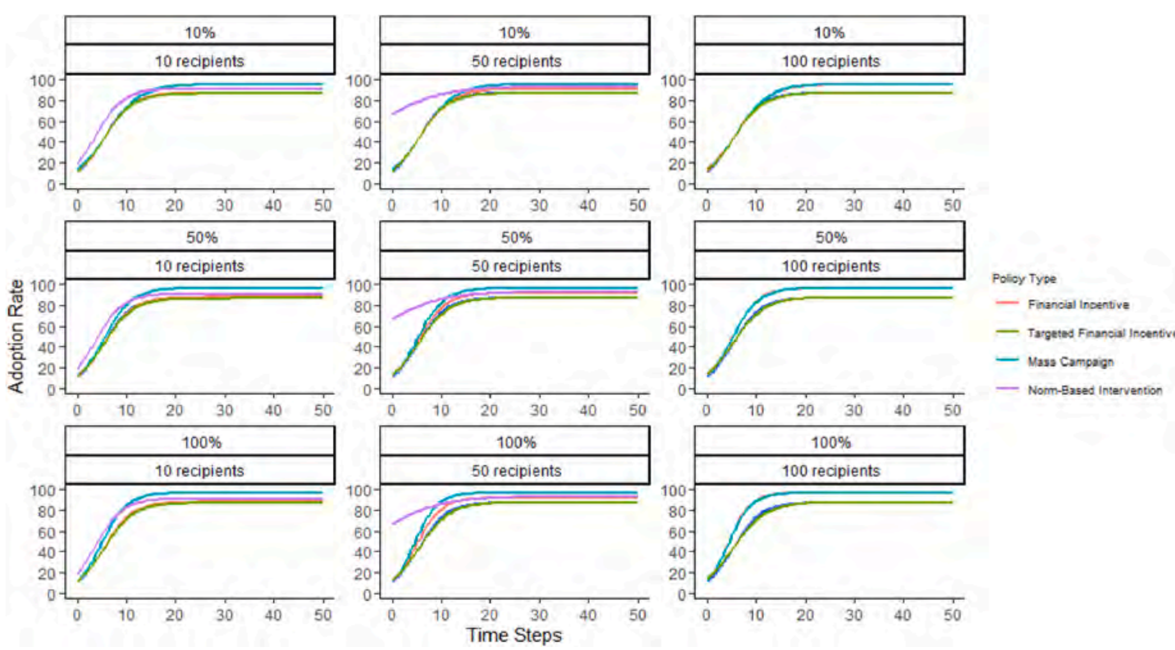

Fig. 14. Policy simulation results for $\beta = 0.7$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

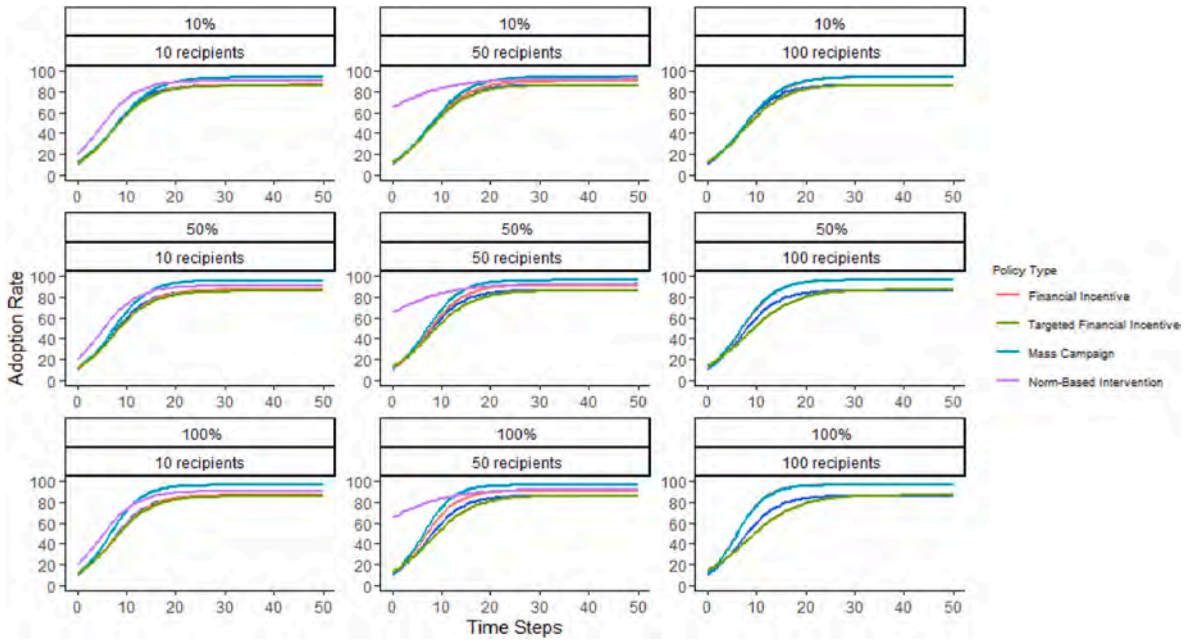

Fig. 15. Policy simulation results for $\beta = 0.8$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

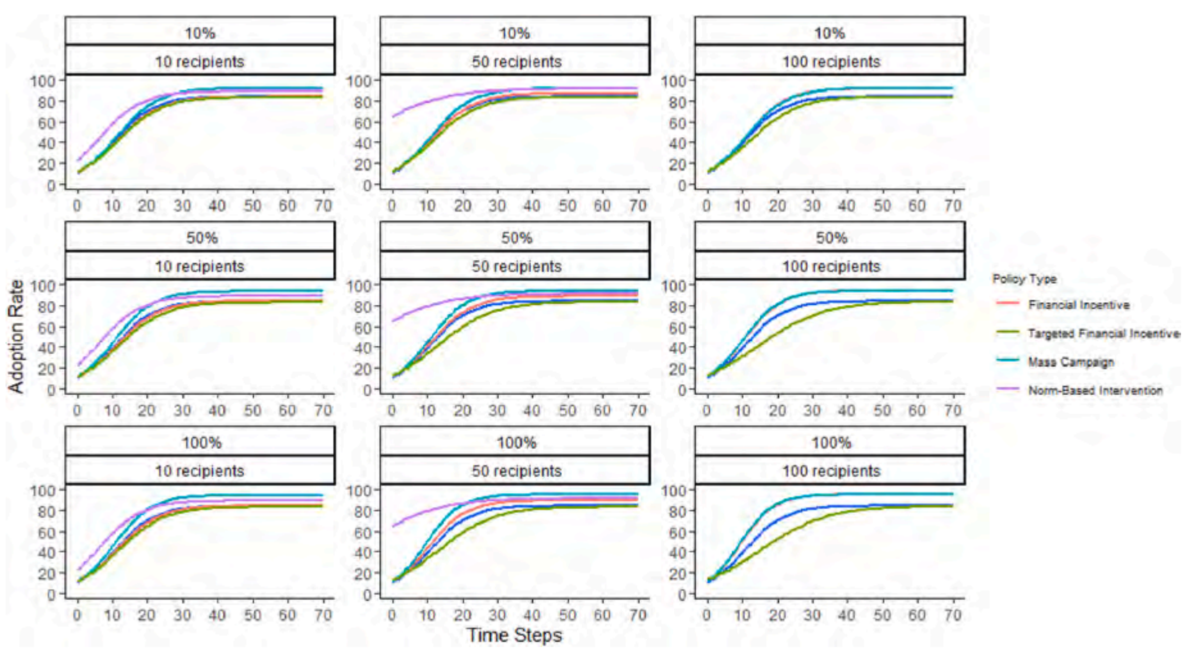

Fig. 16. Policy simulation results for $\beta = 0.9$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

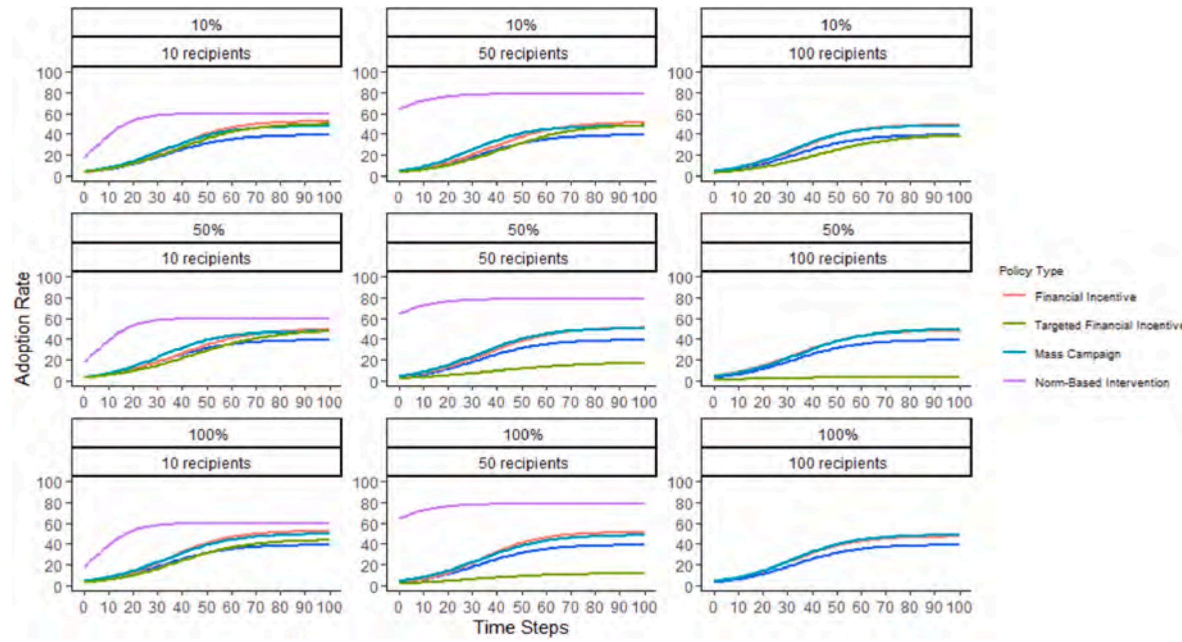

Fig. 17. Policy simulation results for $\beta = 1$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

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