ESSAYS ON ENERGY SAVING TECHNOLOGY ADOPTION CHOICES

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Introduction

This thesis focuses on energy efficient technological adoption choices in the residential sector. It studies form a broad methodological prospective individual and collective decision-making when investing in energy efficient technologies. The thesis starts with an empirical analysis looking at the motivations driving households energy saving choices and continues by developing a theoretical agent-based model to simulate individual technology adoption. The model is then calibrated to specifically study thermal insulation adoption and used to simulate different policy scenarios. Finally, it turns to collective adoption decisions to study the establishment and viability of Renewable Energy Communities. Applying the cooperative game theoretic approach the model shed light on the collective dynamic underlying social innovation processes.

The study of the determinants of energy efficient choices has been conducted both empirically and theoretically. The empirical literature accounts for the motivational attitudes leading to energy saving choices showing that energy saving behaviours are not driven exclusively by rational cost-benefit analysis, but also by less material interests such as environmental motivations.I empirically investigate if household environmental and financial concerns induce to different patterns of adoption of energy saving technologies. I delve further and analyse the socio-economic determinants of adopters, studying if households that reported different degrees of financial and environmental concerns also feature diverse socio-economic profiles. Results show that for high cost technologies environmental motivations do not translate in adoption (i.e. attitude-action gap) and that the socio-demographic profile of environmentally and financially minded individual greatly differs. Results suggest that traditional economic measure aiming at financing building energy renovations should target the most appropriate recipients and might be complement with motivational campaign to achieve greater level of adoption.

In the second chapter, I developed a theoretically based agent-based model to simulate individual technology adoption choices. Traditional economic theory, assuming complete information, homogeneity, and no interaction, postulates an objective weighs up of costs and benefits before choosing the optimal course of action. Conversely, the field of behavioral economics enables to account for the cognitive limitations that bias the decision-making process and to acknowledge individual heterogeneity not only in their preferences but also in their degrees of self-interest and motivations. Finally, the theoretical literature on innovation diffusion considers diffusion as a social contagion process based on imitation but, in most cases, do not thoroughly assess economic motives and cognitive biases. I merged these three main lines of research to account for economic, behavioural and social motivation in technology adoption choices. Starting from the behavioural framework devised by Bénabou and Tirole (2011b), I merged the three streams of literature in an agent-based model that accounts for heterogeneity in economic and behavioural characteristics and decentralized agents' interaction. The model shows that the three approaches are not mutually exclusive and highlights the marginal effect of each of them on the level and pace of adoption. Results show that the traditional adoption curve only emerges when the decision is driven uniquely by social influence, whereas, when economic and behavioral elements are considered, diverse and interesting adoption paths emerge. This implies that studying adoption from a single perspective neglects relevant aspects of both the decision-making and the diffusion process.

In the third chapter, I applied the theoretical agent-based model to study households thermal insulation decision. Data on the financial situation of the household and its environmental concern are used to calibrate economic and behavioural motives. Not observing the actual interaction among households, social motivation is simulated as a diffusion process, i.e. imitation process, on predefined network structures, i.e. preferential-attachment and small-world network topology. The calibrated model is 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. It shows that if retrofit decisions were made only on the basis of economic and behavioural motives, the actual adoption rate would be considerably higher than what is observed in the data. Only when the role of imitation is accounted for, the obtained adoption rate is more similar to the observed level. Therefore households are not perfectly rational, nor are they entirely driven by pro-social motives, rather, they make decisions as actors embedded in social relations. Based on these results, I exploit the agent-based model to simulated three different types of interventions leveraging economic, behavioural, and imitation motives. Results show the relevance of the 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 environmentally concerned and/or do not have access to reliable information. It confirms that enlarging the theoretical framework leads to a more detailed knowledge of the effect of the interventions that in turn suggests to reconsider the design of some established policies.

Finally, the thesis moves from studying diffusion as individual process to a collective one. In order to ensure a comprehensive energy transition, collective investment and ownership are emerging as an available and profitable option to increase the diffusion of renewable energy sources. Large-size decentralized energy systems are too costly for individual households, but can be collectively financed by a group of neighboring households. Renewable Energy Communities (RECs) are collective innovation actions that ensure ownership and control on the produced and consumed energy, increasing the democratization of the energy system. Their establishment provides environmental, economic or social benefits for the community, decreasing the uncertainty of volatile energy prices and increasing the system security. Focusing on the economic benefits of RECs (decrease in electricity bill and network charges), I simulate their establishment relying on coalition formation theory. In the model agents autonomously negotiate in their social network to reach an agreement based on their utility functions. The heterogeneity in consumption behaviors raises the question of equity and stability once the REC is formed. The value created by the community members depends on the level of self-consumption and on the remuneration obtained from injecting the produced energy surplus into the grid, which in turn is affected by the incentive mechanism in place. A community is stable if any households receives more then what he would get if he becomes an individual prosumers. The model therefore tests the stability of RECs under the Italian regulatory framework. Overall, the agent-based model contributes to understand the conditions under which the diffusion of decentralized energy production and consumption can take off and stabilize.

Overall, the thesis suggests that diverse methodological approach should converge to capture synergies and trade-offs between the driving motives of energy efficient adoption choices. A single methodological approach might not be sufficient to represent the complexities involved in the energy system transformation. The thesis therefore focuses on the development of models to generate an understanding of the policy domain. Relying on the complex system approach, informed by different theoretical literature, the thesis shows how it can be used in the policy design process. Based on the issue under investigation, different methods can bring insights on the most effective way to achieve the policy goal. When empirically tested, the agent-based modeling approach shows that a single methodological approach cannot explain the observed patterns and highlights the idea that in order to design effective policy strategies policy-makers should be aware of the consequence a policy might have the different system parts.

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Dedication

This is dedicated to my self, as a personal gift for making it though.

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Chapter 1

The Role of Environmental and Financial Concerns on Energy-Saving Investments.

Alessandra Canepa, Giulia Chersoni, Magda Fontana

Abstract

In this paper we investigate whether households' environmental and financial concerns have any effect on their energy-saving investments. Exploiting a comprehensive dataset covering thirty European countries we investigate if financially concerned and environmentally minded households feature different adoption paths. The results show that environmental and financial concerns play an important role in the decision of adopting energy saving technologies, thus paving the way for policy actions targeted at enhancing consumer awareness. Our analysis also revealed that environmentally and financially concerned households exhibit different socioeconomic profiles. We find that environmentally minded, highly educated households with large family size are more likely to adopt than their counterparts. On the other side, households financial resources are an important factor explaining adoption of economically concerned household. From the methodological point of view our analysis is based on both parametric and non-parametric methods. Namely, we use stochastic dominance analysis to rank distribution functions of household behaviour and logit regression to investigate the socio-economic profile of different groups.

1.1 Introduction

A puzzle of central relevance to energy and climate policy is why in the private residential sector there are still untapped opportunities to reduce energy costs through increased energy efficiency. The economic literature has thoroughly investigated the causes of such under-investment providing a large and variegated body of theory and evidence on the barriers on the adoption of energy efficient technologies (see for example, Jaffe and Stavins (1994); Jaffe et al. (2002)). A growing body of scientific research demonstrates that consumer choices and actions often deviate from the rational choice models which postulates that economic actors objectively weighs up the costs and benefits of all alternatives before choosing the optimal course of action (Kollmuss and Agyeman, 2002). One domain of consumer behaviour where this gap is evident is residential energy use (see for example Flynn et al. (2009)). Kollmuss and Agyeman (2002) refer to this as attitude-action gap to indicate a situation where there is a misalignment between consumer attitude and consumer practical steps to reduce household energy consumption. The authors suggest that in many cases individuals' awareness about environmental problems does not translate into pro-environmental choices.

Against this background, in this paper we contribute to the debate by examining the role of environmental and financial attitudes on the adoption of energy saving technologies. Exploiting data from the *Second consumer market study on the functioning of the retail electricity markets for consumers in the EU* (DG-Justice, 2016) that covers thirty European countries, we investigate if households' environmental and financial concerns have an impact on adoption of energy saving technologies. Questions we are trying to answer in this work are the following: Do financially and environmentally concerned household show different patterns of adoption? A closely related question is: Does a statement of being environmentally minded or financially constrained actually induces individuals and households to engage in the adoption of energy saving technologies? In other words, does awareness translates to action? Moreover, there is substantial evidence that households' decisions to invest in energy saving technology heavily depend on socio-economic factors (see Schleich (2019); Urban and Ščasnỳ (2012); Trotta (2018) among others). Accordingly, a second objective of this paper is to investigate if socio-economic determinants of adoption are different for financially and environmentally minded households. To account for financial constraints in the household decision making process, we consider three energy saving technologies of increasing cost, namely low cost low-energy bulbs, middle cost energy-efficiency appliances, and investment in thermal insulation of private buildings which constitutes the most expensive form of energy saving technology.

Household attitude towards financial and environmental concerns on the decision of adoption has important policy implications. It is therefore not surprising that many empirical studies have investigated the matter (for a review see for example Kastner and Stern (2015). However, most of the literature focuses on one issue or another. We believe that financial and environmental concerns are two faces of the same coin. In this respect, considering the joint impact of household environmental and financial concerns on the decision of adoption may shed some light on the puzzle that has plagued academics and policy makers alike in the recent years.

Our empirical investigation proceeds in two steps. In the first stage, we investigate if household environmental and financial concerns induce to different patterns of adoption of energy saving technologies. Unlike the previous literature, we use stochastic dominance methodology to determine if environmental and financial motivations affect household behaviour. Stochastic dominance is a non parametric procedure that allows us to compare distribution functions of different adoption levels within groups of households. It allows us to answer questions like: Is what individual say actually what they do when it comes to investment decisions in energy saving technologies? In doing so we are in a position of testing for the attitude-action gap hypothesis postulated by theoretical models. Having examined if environmental and financial concerns induce to different patterns of adoption of energy saving technologies, in the second stage we delve further and analyse the socio-economic determinants of adoption. In this stage we are particularly interested in investigating if households that reported different degrees of financial and environmental concerns also feature diverse socio-economic profiles. To examining this issue, we turn to a parametric model specification and estimate the probability of the adoption of environmentally and financially minded households as a function of a number of socio-economic factors. In line with the extant literature covariates include socio-economic factors such as age, gender, education, family size, and income (Kastner and Stern, 2015; Mills and Schleich, 2010; Urban and Ščasnỳ, 2012).

The present paper extends the existing literature in several ways. First, the results of the stochastic dominance analysis show that environmental and financial concerns play an important role in the decision of adopting energy saving technologies, thus paving the way for policy actions targeted at enhancing consumer awareness. Second, the parametric analysis reveals that environmentally and financially concerned households exhibit different socioeconomic profiles. We find that environmentally minded, highly educated households with large family size are more likely to adopt than their counterparts with low level of education ans smaller families. On the other side, difficult financial situations are an important factor explaining adoption of economically concerned household, while more affluent households tend to be more environmentally concerned. The proposed methodological approach is the third contribution of the paper. The stochastic dominance procedure adopted in this paper is extremely flexible as it is robust to departures of cross-dependency between random variables, serial correlation and unconditional heteroscedasticity (see Linton et al. (2005)). Finally, unlike many other related studies, our analysis is based on a novel dataset that covers a large number of countries across Europe. This large sample allow us to overcome idiosyncratic factors and exploit the heterogeneity across countries. Such comprehensive level of analysis is rarely found in related empirical works.

The paper is structured as follows. Section 1.2 describes the theoretical background in the light of the related literature. Section 1.3 illustrates the data used in the analysis. Section 1.4 introduces the stochastic dominance procedure and the empirical specification of the regression model. Section 1.5 discusses the empirical results. Finally, Section 1.6 presents some concluding remarks and policy implications.

1.2 Literature on Energy Saving Behaviours

A major challenge for academic and policy makers has been how to encourage consumers to adopt environmentally friendly technologies. This is because the motivation that leads consumers to adopt energy saving activities is complex and not easily identified. The extant literature indicates that explaining energy consumption and conservation behaviours is so complex that it is difficult to capture in a single framework (Kollmuss and Agyeman, 2002). Moreover, while the empirical evidence pinpoints that some variables may be better predictor of energy consumption than other, the findings have been far from consistent across time, context, samples, and studies (for a review see (Frederiks et al., 2015)).

It is clear however, that energy saving behaviours are not driven exclusively by rational cost-benefit analysis, but also by less material interests such as knowledge and motivations (Steg et al., 2015). In this respect, the relevant literature makes a distinction between two types of residential energy-saving activities: efficiency investments and curtailments (Barr et al., 2005). Curtailments focus over everyday reduction of energy usage that require either no or minimal structural adjustments (e.g. thermostat settings, switching off lights), while efficiency investments are often long-term structural alteration that require financially and normally technical resources to be utilized. The amount of financial and other resources can vary greatly among investment choices, ranging from insulation, purchase of energy saving products, and usage of low-energy light bulbs. Jansson et al. (2009) argue that unlike curtailment, efficiency investments are high involvement activities, which require considerable monetary costs for their implementation. For this reason, the authors suggest that decisions to introduce efficiency measures are less driven by moral motivation than curtailment. Yet, many people do engage in such behaviours (Steg et al., 2015). Therefore, what motivates people to engage in costly or effortful energy saving behaviours remains an open question.

A great number of studies provides evidence on the importance of cost-reduction factors (e.g. reducing energy bills, paying less for energy-efficiency appliances) as drivers for energy saving investments (Schleich, 2019; Trotta, 2018; Aravena et al., 2016; Nair et al., 2010). However, available empirical investigations offer a less clear-cut evidence on the role of environmental concerns on the adoption of energy saving technologies, providing sometimes controversial results. In the literature, there is general agreement on the fact that the impact of environmental concerns is greater for low cost technologies, so that the attitude-action gap is lower for these technologies (Kastner and Stern, 2015; Pothitou et al., 2016; Whitmarsh, 2009). However, some studies found that environmental motivations have an impact on high and medium cost technologies such as photovoltaic systems and energy efficiency appliances. For example, some authors found that environmental concerns and knowledge of renewable energies positively increases the probability of adoption of photovoltaic systems (Schleich, 2019; Bergek and Mignon, 2017b; Bashiri and Alizadeh, 2018b), and the installation of energy efficient appliances (Urban and Ščasnỳ, 2012; Cheung et al., 2017; Mills and Schleich, 2010).

Consensus literature highlights the fact that environmental and financial concerns are also related to socioeconomic factors. For example, low-income households with low level of education are found to be more motivated to save energy for financial reasons, as well as households members 65 years of age or older (Mills and Schleich, 2012). On the other hand, aged and educated individuals (Shen and Saijo, 2008; Urban and Ščasnỳ, 2012), as well as families with young children (Mills and Schleich, 2012), are more likely to be more environmentally concerned, while male with high per capita income are found to be generally less concerned about the environment (Urban and Ščasnỳ, 2012). In the same vein, Poortinga et al. (2002) use socio-demographic variables to explain household energy consumption, finding that factors such as income and household size play an important role in the adoption decision.

However, comparing findings across studies is difficult as they differ with respect to the types of technologies, explanatory variables, and methods. Moreover, since the technological, social, cultural and policy environment develop over time, a comparison across studies carried in different point in time might be misleading (Mills and Schleich, 2012). To the best of the authors knowledge, none of the mentioned studies have attempted to study the role of environmental and financial concerns on energy saving behaviours in a multi-country context comparing their effect on different energy saving investments. Mills and Schleich (2012) performed a similar analysis but focusing on a smallest set of dependent variable and, similar to Urban and Ščasnỳ (2012), attitudes are not compared by increasing technology costs.

1.3 Data

This study exploits data from the *Second consumer market study on the functioning of the retail electricity markets for consumers in the EU* (DG-Justice, 2016) that investigates consumers' awareness, attitude and experience with electricity services. The survey, in the form of questionnaire, was targeted to individuals (aged from 18 to 95) who were fully or jointly in charge of paying the electricity bill in their household. The original dataset includes 29,119 interviews conducted with a mixed-mode approach (online, telephone, and face-to-face) across 30 European countries (EU28 plus Iceland and Norway). To ensure that the sample in each country was representative for the targeted population, quotas over age, gender and region were set. After data cleaning our sample includes 23,808 households.

The dataset collects information on households energy saving investments going form low-cost energy efficient technologies (i.e. energy saving light bulbs) to high-cost technologies (home insulation), though medium-costs investments (energy efficient appliances). Specifically, we extracted the following information:

- Bought energy saving light bulbs: Yes or No
- Bought energy efficiency appliances: Yes or No
- Had your home (re-)insulated: Yes or No

To account for the different financial resources required to adopt those technologies, the adoption of energy efficient appliances and of light emitting diodes is explored for tenants and homeowners, whereas insulation measures are considered for home-owners only. It permits to avoid the split-incentives problem, which is typically related to high-cost investment (Melvin, 2018; Castellazzi et al., 2017).

The literature on environmental concern generally conceptualize it as an attitude toward environmental issues (Dunlap et al., 2002). In this study households environmental attitude refers specifically to energy saving behaviours and is measured by households stated importance of energy saving for environmental reasons. The dataset covers also households importance for energy saving due to financial reasons, related to the cost reduction associated with energy efficiency measures (see for example Schleich (2019)). Environmental and financial concerns were detected by selecting the following questions in the questionnaire:

- It is important for me to save energy for environmental reasons
- It is important for me to save energy for financial reasons

Respondents indicate on a 11-point Likert-scale variable, ranging from "totally disagree" to "10 -totally agree", their financial and environmental attitudes toward energy savings. We re-arranged the information contained in the original dataset in three groups: low (0-3), medium (4-7), and high (8-10) financial and environmental attitudes. Panels A and B in Table 1.1 reports the descriptive statistics of the above mentioned variables.

Table 1.1: Descriptive Statistics: Technologies and Attitudes

	N	%
Panel A: Technologies		
Energy saving light bulbs		
Non adopters	3088	12.97
Adopters	20720	87.03
Energy-efficient appliances		
Non adopters	5981	25.12
Adopters	17827	74.88
Home reinsulated		
Non adopters	15572	65.41
Adopters	8236	34.59
Panel B: Attitudes		
Financially minded		
Low	1542	6.48
Medium	6420	26.97
High	15846	66.56
Environmentally minded		
Low	2176	9.14
Medium	8265	34.72
High	13367	56.14

The dataset covers also a set of socio-demographic characteristics that are normally associated with households propensity to invest in energy efficiency measures. In the literature the factors influencing energy saving activities are generally categorized as characteristics of the household (e.g. education, income, number of children, age, renter or owner), characteristics of the residence (multi-family home, size), characteristics of the measure (behavioral or technological, costs, performance, energy use), economic factors (energy prices), availability and quality of information, weather and climate factors, and attitudes towards energy savings or towards the environment (Mills and Schleich, 2012). Table 1.2 describes the sample and the available information extracted from the survey.

Table 1.2: Descriptive Statistics: Socio-demographic characteristics

	N	%
Panel C: Socio-demographic characteristics		
Age	23080	42.05
Gender		
Man	11672	49.03
Woman	12136	50.97
Education		
Low	2984	12.53
Medium	10900	45.78
High	9924	41.68
Population density		
Low (100 inhab /sqkm)	6613	27.78
Medium (100 - 499 inhab /sqkm)	7193	30.21
High (500 inhab /sqkm)	10002	42.01
Ownership status		
Owner	16685	70.08
Tenant	4090	17.18
Social Housing	1440	6.05
Other	1593	6.69
Financial situation		
Very easy	2514	10.56
Fairly easy	9070	38.1
Not easy	9558	40.15
Not easy at all	2666	11.2
Household size		
1	9178	38.55
2	6471	27.18
3	5495	23.08
4	1901	7.98
More then 4	679	3.2
Children		
0	14152	59.44
1	5281	22.18
2	3417	14.35
3	768	3.23
More then 3	190	0.80

1.4 Methods

1.4.1 Stochastic dominance

This section presents the conceptual framework for the stochastic dominance procedure. Following standard consumer theory, we assume that households maximize their utility function either: i) by minimizing energy costs for financial reasons, or ii) by minimizing adverse environmental effects related to their energy consumption; or iii) they can have both objectives i) and ii) in their utility function. In particular, households can increase their welfare by making three types of energy efficiency investments with an increasing monetary cost from low to high. The first type of energy saving investment is classified as low-cost and corresponds to the adoption of low emitting energy bulbs, which we refer to as *Lights*. The second type of energy saving investment is the medium-cost adoption of energy-efficiency appliances, which we label as *Appliances*. Finally, the most expensive energy saving technology considered is the investment in thermal insulation, which we refer to as *Insulation* hereafter.

Formally, let X_1 and X_2 be two random variables related to adoption of a given energy saving technology and $F_1(x)$ and $F_2(x)$ their cumulative distribution functions.First order stochastic dominance implies that all utility maximizing households will prefer X_1 to X_2. Second order stochastic dominance implies the usual assumption of diminishing marginal utility, a negative second derivative of the household's utility function Testing for stochastic dominance is based on comparing the cumulate distribution functions of the random variables related to households' attitudes toward financial and environmental issues. However, the true cumulated distribution functions are not known in practice. Therefore, stochastic dominance tests rely on the empirical distribution functions. In the literature several procedures have been proposed to test for stochastic dominance [1]. In this paper we use the inference procedure suggested in Linton et al. (2005) where consistent critical values for testing stochastic dominance are obtained for serially dependent observations. The procedure also accommodates for general dependence amongst the prospects which are to be ranked.

To investigate whether households' environmental and financial concerns have an impact on the adoption of energy saving technologies the hypotheses test compares the behaviour of adopting and non adopting households and their related motivations. Let Ω be the set of households that adopted at least one energy saving technologies. Let $\left\{X_{i,j} : x_{i,j} \subseteq \Omega\right\}$ and $\left\{\overline{\overline{X}}_{i,j} : \overline{\overline{x}}_{i,j} \subseteq \Omega\right\}$ the subsets of adopting households that expressed high and low (or no) concern, respectively, in the i motivation, for $i = 1, 2$ (i.e. financially concerned, environmentally minded) and let j be the energy-saving technology, for $j = 1, ..., 3$ (i.e., lights, appliances, insulation). Let Ψ represents the set of households that did not adopt energy saving technologies, so that $\left\{Y_i, j : y_{i,j} \subseteq \Psi\right\}$ and $\left\{\overline{\overline{Y}}_{i,j} : \overline{\overline{y}}_{i,j} \subseteq \Psi\right\}$ denote the subsets of non-adopting households that expressed high and low concern in i the matter, respectively.

[1]An early work by McFadden (1989) proposed a generalization of the Kolmogorov-Smirnov test of first and second order stochastic dominance among several prospects (distributions) based on i.i.d. observations and independent prospects. Later works by Klecan et al. (1991) and Davidson and Duclos (2000) extended these tests allowing for dependence in observations and replacing independence with a general exchangeability amongst the competing prospects.

Below, we first state the hypotheses under investigation and we then describe the testing procedure for stochastic dominance adopted in the paper (see Appendix A for a summary of the hypotheses).

Proposition 1: *Highly concerned households adopt more environmentally sustainable technologies than little (or no) concerned households.*

For each technology j, we test the hypothesis that adoption from highly concerned households stochastically dominates the adoption level of households that expressed low (or no) level of concern. That is to say that positive attitudes leads to higher adoption. To establish the direction of stochastic dominance between $X_{i,j}$ and$\overline{\overline{X}}_{i,j}$ we test the following null hypotheses

$$H_0^1 : X_{i,j} \succ_s \overline{\overline{X}}_{i,j} \text{ and } H_0^2 : \overline{\overline{X}}_{i,j} \succ_s X_{i,j}$$

where the operator $\succ_s$ indicates the dominance relation, with the alternative hypotheses being the negation of the null hypothesis for both H_0^1 and H_0^2. We infer that households that expressed high level of concern in the i matter (positive attitudes) stochastically dominate (adopts more then) households that expressed low level of concerns in the same matter if we accept H_0^1 and reject H_0^2. Conversely, we infer that households that expressed low level of concern (no or low attitudes) stochastically dominate (adopts more then) households that expressed high level of concern in the i matter if we accept H_0^2 and reject H_0^1. In cases where neither of the null hypotheses can be rejected, we conclude that the stochastic dominance test statistic is not conclusive.

Proposition 2: *Strong financial concerns translate to greater adoption of energy saving technologies.*

Proposition 3: *Households with positive attitude towards environmental matters adopt more than households with little (or no) concerns toward environmental problems.*

Proposition 2 and 3 state that households with high concern in the i matter stochastically dominate non adopting households with low (or no) concerns in the same matter. These propositions are meant test for the attitude-action gap hypothesis suggested for example in Flynn et al. (2009). To assess of the validity of these propositions we consider adopting and non-adopting households and test the following null hypotheses:

$$H_0^1 : X_{i,j} \succ_s \overline{\overline{Y}}_{i,j} \text{ and } H_0^2 : \overline{\overline{Y}}_{i,j} \succ_s X_{i,j}$$

with the alternative hypotheses being the negation of the null hypothesis for both H_0^1 and H_0^2. For each technology j, we conclude that the adoption for households that are highly concerned in the matter i stochastically dominate (adopt more then) not adopting households with low concern if we accept H_0^1 and reject H_0^2. On the other hand, we infer that non adopting households with low concern in i matter stochastically dominate (adopt more then) adopting households with low concern in the same matter if we accept H_0^2 and reject H_0^1. In cases where neither of the null hypotheses can be rejected, we conclude that the stochastic dominance test statistic is not conclusive.

Corollary 1: *Low financial concerns lead households to not adopt energy saving technologies.*

Corollary 2: *Negative attitude toward environmental problems leads households to not adopt energy saving technologies.*

Corollaries 1 and 2 are nuances of Proposition 2 and 3 since they state that non-adopting households that expressed low (or no) concern in the i matter stochastically dominate (adopt more then) adopting households with a similar level of concern in the same matter. The validity of these propositions can be assessed by testing that following null hypotheses

$$H_0^1 : \overline{\overline{Y}}_{i,j} \succ_s \overline{\overline{X}}_{i,j} \text{ and } H_0^2 : \overline{\overline{X}}_{i,j} \succ_s \overline{\overline{Y}}_{i,j}$$

with the alternative hypotheses being the negation of the null hypothesis for both H_0^1 and H_0^2.

Proposition 4: *Strong financial and environmental concerns jointly lead to higher adoption of energy saving technologies.*

Proposition 4 states that adopting households that expressed jointly strong financial and environmental concerns adopt more then adopting households with low (or no) concerns in both matters. To assess the empirical validity of Proposition 4 we consider the intersection, $\Theta_j = X_{E,j} \cap X_{F,j}$, the subsets of adopting households that are jointly highly financially and environmentally concerned, and the intersection $\overline{\overline{\Gamma}}_j = \overline{\overline{X}}_{E,j} \cap \overline{\overline{X}}_{F,j}$, the subset of households neither (or little) environmentally nor financially concerned, and test the following hypotheses:

$$H_0^1 : \Theta_j \succ_s \overline{\overline{\Gamma}}_j \text{ and } H_0^2 : \overline{\overline{\Gamma}}_j \succ_s \Theta_j$$

with the alternative hypotheses being the negation of the null hypothesis for both H_0^1 and H_0^2.

Corollary 3: *Households that are jointly strongly concerned about the environmental and financial matters adopt more than households that expressed little (or no) concerns.*

Corollary 3 is closely related to Propositions 2 and 3 in the sense that we test the same hypotheses, but this time we consider the subset of households that expressed both environmental and financial concerns. Let $\overline{\overline{\Upsilon}}_j = \left(\overline{\overline{Y}}_{E,j} \cap \overline{\overline{Y}}_{F,j}\right)$ where $\overline{\overline{Y}}_{E,j}$ and $\overline{\overline{Y}}_{F,j}$ are the subsets of households that did not adopt energy saving technologies and expressed low (or no) concerns on environmental and financial matters, respectively. To investigate the validity of Corollary 3, we test the hypothesis that adopting households with low (or no) concerns in the both matters adopt more then non-adopting households with similar level of concern in both matters. Therefore, the null hypotheses are:

$$H_0^1 : \Theta_j \succ_s \overline{\overline{\Upsilon}}_j \text{ and } H_0^2 : \overline{\overline{\Upsilon}}_j \succ_s \Theta_j$$

with the alternative hypotheses being the negation of the null hypothesis for both H_0^1 and H_0^2.

Corollary 4: *Negative attitude toward the environment and low financial concern lead households to avoid adopting energy saving technologies.*

For completeness, Corollary 4 states that non-adopting households that expressed low (or no) concerns in both matters stochastically dominate adopting households that jointly expressed low (or no) concerns in both matters. To assess this proposition, we test the following null hypotheses

$$H_0^1 : \overline{\overline{\Upsilon}}_j \succ_s \overline{\overline{\Theta}}_j \text{ and } H_0^2 : \overline{\overline{\Theta}}_j \succ_s \overline{\overline{\Upsilon}}_j$$

where $\overline{\overline{\Theta}}_j = \left(\overline{\overline{X}}_{E,j} \cap \overline{\overline{X}}_{F,j}\right)$ and $\overline{\overline{X}}_{E,j}$ and $\overline{\overline{X}}_{F,j}$ are the subsets households that did adopt energy saving technologies and expressed low (or no) concerns on environmental and financial matters, respectively. As before the alternative hypotheses are the negation of the null hypothesis for both H_0^1 and H_0^2.

Proposition 5: *Financial concerns lead to greater adoption than environmental concerns.*

In Proposition 5 we assess the hypotheses that financial concerns overtake environmental concerns in the decision of adopting energy saving technologies. In the literature it is not clear if in the motivation that leads households to adopt energy saving technologies financial matters impact more than environmental concerns. For example, Whitmarsh (2009) finds that economic factors overtake environmental motivations as driving factors for curtailments and energy investments. However, the literature is not conclusive on the motivations that lead households to adopt energy-saving activities (see (Steg et al., 2015)). For this reason, under the null hypotheses we state that:

$$H_0^1 : \overline{\overline{X}}_{F,j} \succ_s X_{E,j} \text{ and } H_0^2 : X_{E,j} \succ_s \overline{\overline{X}}_{F,j}$$

with the alternative hypotheses being the negation of the null hypothesis for both H_0^1 and H_0^2.

Corollary 5: *Households with low (or no) financial concerns adopt more than households with little (or no) environmental concerns.*

Finally, Corollary 5 tests the hypothesis that even when households express low (or no) concerns, financial matters overtake environmental matters when it comes to investment decisions in energy saving technologies. Accordingly, we state the following null hypotheses:

$$H_0^1 : \overline{\overline{X}}_{F,j} \succ_s \overline{\overline{X}}_{E,j} \text{ and } H_0^2 : \overline{\overline{X}}_{E,j} \succ_s \overline{\overline{X}}_{F,j}$$

with the alternative hypotheses being the negation of the null hypothesis for both H_0^1 and H_0^2.

1.4.2 Logit

Consensus literature supports the view that demographic and socio-economic factors play a major role on consumer behaviour. For example, factors such age, gender, education level and income were found to increase the probability of adoption (Urban and Ščasnỳ, 2012; Pothitou et al., 2016; Schleich, 2019). However, the influence of socio-demographic characteristics on individual environmental and financial attitudes is a less examined topic (Mills and Schleich, 2012; Shen and Saijo, 2008; Urban and Ščasnỳ, 2012).

Against this background, we now turn to parametric modelling and estimate a logit model to further delve on the relationship between the financial and environmental concern investigated in this paper and the profile of economic agents. Therefore, we study the influence of households socio-demographic characteristics on their environmental and financial attitudes related to energy saving investments of increasing costs (i.e. *Lights*, *Appliances*, *Insulation*). For the k household, the i concern, and the technology j, the probability of being environmentally or financially concerned is given by:

$$\pi_{k,i,j} = Pr(Adopt_{k,i,j}|X_k = x_k) = \frac{e^{x'_{k\beta}}}{1 + e^{x'_{k\beta}}}$$

where the dependent variable, $\pi_{k,i,j}$, is the probability of being environmentally or financially concerned conditional to the adoption of the technology j and to the vector X of covariates (see Section 1.5.2 for the covariates specification) [2].

1.5 Results

1.5.1 Stochastic dominance results

Table 1.3 reports the results of the stochastic dominance test in relation to the propositions stated in section 1.4.1. In particular, columns 1 and 2 report the propositions under assessment and the corresponding null hypotheses, while columns 3-8 report the p-values of the stochastic dominance test in relation to the three different energy saving technologies considered. The p-values are reported for the first and second order stochastic dominance referred to as "FSD" and "SSD", respectively [3].

Proposition 1 tests the investment behaviours of highly and not concerned adopting households. Looking at the results it appears that consumers' attitudes play an important part in the adoption of energy saving technologies as the null hypotheses $H_0^1 : X_{i,j} \succ_s \overline{\overline{X}}_{i,j}$ are not rejected. Conversely, the null hypotheses $H_0^2 : \overline{\overline{X}}_{i,j} \succ_s X_{i,j}$ are rejected in favour of the alternative hypotheses, meaning that we have to reject the hypothesis that low or no concerned households adopt more than highly concerned households. Therefore, we conclude that highly concerned adopting households stochastically dominate adopting households that expressed low (or no) concern in financial or environmental matters. Remarkably, this result holds no matter the cost of the technology under consideration and the order of stochastic dominance: highly concerned adopting households adopt more energy saving technologies then those with low or no level of concern.

Coming now to Propositions 2 and 3 we can see that the results in Table 2 highlights important differences when the cost of adopting energy saving technologies is taken into consideration. The propositions test the behaviour of highly concerned adopting households against low or not concerned not adopting households. With respect to Proposition 2, the null hypotheses $H_0^1 : X_{F,j} \succ_s \overline{\overline{Y}}_{F,j}$ are not rejected at first order stochastic dominance for all three technologies, whereas $H_0^2 : \overline{\overline{Y}}_{F,j} \succ_s X_{F,j}$ are rejected in all cases. Therefore, we conclude that highly financially

[2]The analysis as a descriptive purpose, as we cannot rule out the omitted variables bias and confounding effect.
[3]The p-values are obtained using the non- parametric block-bootstrap method with $B = 1000$ replications.

Table 1.3: Test for Stochastic dominance results.

	Null Hypotheses	***Energy saving technologies***					
		Bulbs		***Appliances***		***Insulation***	
		FSD	SSD	FSD	SSD	FSD	SSD
Prop 1	$H_0^1 : X_{F,j} \succ_s \overline{\overline{X}}_{F,j}$	0.962	0.554	0.999	0.935	0.999	0.941
	$H_0^2 : \overline{\overline{X}}_{F,j} \succ_s X_{F,j}$	0.000	0.001	0.000	0.000	0.000	0.000
	$H_0^1 : X_{E,j} \succ_s \overline{\overline{X}}_{E,j}$	0.999	0.985	0.999	0.982	0.666	0.961
	$H_0^2 : \overline{\overline{X}}_{E,j} \succ_s X_{E,j}$	0.000	0.000	0.000	0.000	0.000	0.000
Prop 2	$H_0^1 : X_{F,j} \succ_s \overline{\overline{Y}}_{F,j}$	0.950	0.637	0.999	0.949	0.999	0.987
	$H_0^2 : \overline{\overline{Y}}_{F,j} \succ_s X_{F,j}$	0.000	0.002	0.000	0.000	0.000	0.000
Prop 3	$H_0^1 : X_{E,j} \succ_s \overline{\overline{Y}}_{E,j}$	0.999	0.652	0.711	0.952	0.000	0.000
	$H_0^2 : \overline{\overline{Y}}_{E,j} \succ_s X_{E,j}$	0.000	0.000	0.000	0.000	0.697	0.896
Corol 1	$H_0^1 : \overline{\overline{Y}}_{F,j} \succ_s \overline{\overline{X}}_{F,j}$	0.000	0.000	0.653	0.684	0.795	0.595
	$H_0^2 : \overline{\overline{X}}_{F,j} \succ_s \overline{\overline{Y}}_{F,j}$	0.999	0.889	0.865	0.577	0.071	0.019
Corol 2	$H_0^1 : \overline{\overline{Y}}_{E,j} \succ_s \overline{\overline{X}}_{E,j}$	0.000	0.000	0.538	0.205	0.999	0.967
	$H_0^2 : \overline{\overline{X}}_{E,j} \succ_s \overline{\overline{Y}}_{E,j}$	0.999	0.972	0.981	0.927	0.000	0.000
Prop 4	$H_0^1 : \Theta_j \succ_s \overline{\overline{\Gamma}}_j$	0.999	0.969	0.999	0.956	0.999	0.983
	$H_0^2 : \overline{\overline{\Gamma}}_j \succ_s \Theta_j$	0.000	0.000	0.000	0.000	0.000	0.000
Corol 3	$H_0^1 : \Theta_j \succ_s \overline{\overline{\Upsilon}}_j$	0.999	0.979	0.999	0.968	0.000	0.000
	$H_0^2 : \overline{\overline{\Upsilon}}_j \succ_s \Theta_j$	0.000	0.000	0.000	0.000	0.999	0.963
Corol 4	$H_0^1 : \overline{\overline{\Upsilon}}_j \succ_s \overline{\overline{\Theta}}_j$	0.999	0.987	0.237	0.563	0.000	0.000
	$H_0^2 : \overline{\overline{\Theta}}_j \succ_s \overline{\overline{\Upsilon}}_j$	0.000	0.000	0.945	0.688	0.994	0.973
Prop 5	$H_0^1 : \overline{\overline{X}}_{F,j} \succ_s X_{E,j}$	0.745	0.796	0.922	0.629	0.934	0.549
	$H_0^2 : X_{E,j} \succ_s \overline{\overline{X}}_{F,j}$	0.937	0.528	0.882	0.554	0.000	0.002
Corol 5	$H_0^1 : \overline{\overline{X}}_{F,j} \succ_s \overline{\overline{X}}_{E,j}$	0.000	0.003	0.888	0.716	0.268	0.660
	$H_0^2 : \overline{\overline{X}}_{E,j} \succ_s \overline{\overline{X}}_{F,j}$	0.986	0.686	0.624	0.455	0.945	0.452

concerned adopting households first order stochastically dominate not adopting households that expressed low (or no) interest on energy savings due to financial reasons. Looking at Proposition 3, the results related to low-to-medium costs energy saving technologies are not different. However, when it comes to investing in costly property thermal insulation the null hypothesis $H_0^1 : X_{E,j} \succ_s \overline{\overline{Y}}_{E,j}$ cannot be rejected, whereas the null hypothesis $H_0^2 : \overline{\overline{Y}}_{E,j} \succ_s X_{E,j}$ is rejected in favour of the alternative hypothesis. We thus conclude that not-adopting households with low environmental concerns first order stochastically dominate adopting households with low (or no) environmental concerns. The result that economic factors have a greater impact on the adoption of energy saving technologies than environmental factors for high investment costs is also found in related literature (see for example Whitmarsh (2009)), confirming the attitude-action gap hypothesis for high-cost technologies.

The assessment of the validity of Corollary 1 and 2 gives mixed results for the data at hand. From column 3 and 4 in Table 1.3 we do not reject the null hypotheses $H_0^1 : \overline{\overline{Y}}_{i,j} \succ_s \overline{\overline{X}}_{i,j}$ but we do reject the null hypotheses $H_0^2 : \overline{\overline{X}}_{i,j} \succ_s \overline{\overline{Y}}_{i,j}$. Therefore, we can infer that in the case of adoption of low-cost technology, low level of financial or environmental concerns still lead households to adopt energy saving technologies. However, the picture changes when we consider more expensive technologies such as thermal insulation, where we do no reject the null hypothesis that $H_0^2 : \overline{\overline{X}}_{i,j} \succ_s \overline{\overline{Y}}_{i,j}$ but the hypothesis $H_0^1 : \overline{\overline{Y}}_{i,j} \succ_s \overline{\overline{X}}_{i,j}$ can be rejected. Therefore, in this case we can conclude that low motivation toward environmental or financial matters leads households to act accordingly and not to invest in expensive insulation measures. Interestingly enough, the test results for the middle cost energy efficient appliances are not conclusive as in column 5 and 6 both null hypotheses can't be rejected.

Regarding Proposition 4, from Table 1.3 we can infer that adopting households that are highly concerned in both environmental and financial matters first order stochastically dominate their counterpart with low (or no) concerns, no matter the cost of the technology under consideration. In this respect, these results are consistent with the conjecture in Proposition 1, where environmental and financial concern were considered separately. The results from the assessment of Proposition 4 can only strength our conclusion that positive attitude toward environmental or financial matters increase households' energy-saving investments. The same results hold true for Corollary 3 where the findings exactly match with those for Proposition 2 and 3, thus strengthening the validity of our conjectures. Technological costs matters, when high the decision to insulate the home is not supported by households' attitudes. Corollary 4 tests the hypothesis that low attitude toward environment and financial concerns lead households to avoid adopting energy saving technologies. Results match those of Corollary 1 and 2, reinforcing the idea that for low cost technologies, low concern in both matters still lead to adoption, while households with low level of concern act accordingly and do not adopt high-cost energy saving technologies. For medium-cost technologies the results are still inconclusive.

Finally, coming to Proposition 5, from Table 1.3 we can compare the relative effect of financial and environmental concerns on adoption. From the results, we can infer that financial motivations are important when it comes to adoption of costly insulation technology, but in the case of adoption of less expensive technologies there is no clear winner since in the latter case the stochastic dominance tests are not conclusive. In other words, a statement of "high concern" in environmental matters translates to action only for low-to-middle cost technologies, but not for costly thermal insulation technology. This result is reinforced when we look at the test results for Corollary 5, which test the hypothesis that households with low (or no) financial concerns adopt more than house- holds with little (or no) environmental concerns. In this case we do not reject the null at first order only for the hypothesis $H_0^2 : \overline{\overline{X}}_{E,j} \succ_s \overline{\overline{X}}_{F,j}$ for the adoption low energy saving investments only, whereas for the other more expensive technologies the test statistic is not conclusive. Therefore, we conclude that households with low (or no) environmental concerns stochastically dominate households with low (or no) financial concerns for the adoption of the low-cost bulbs only.

1.5.2 Financial and environmental concern and socio-economic determinants

In Section 1.5.1 the stochastic dominance analysis has revealed several insights on the impact of financial and environmental concerns on the adoption patterns of energy saving technologies. However, the non parametric analysis is rather silent on the socio-economic background of adopting households. To establish the empirical relationship between households' preferences for energy savings for environmental and financial reasons and households characteristics, we turn into a parametric analysis. Specifically, we econometrically estimate a regression model employing the set of independent variables described in Table 1.2 and accounting for country specific effects.

In order to select the covariates to include into the regression model we performed a stepwise logistic regression [4] Therefore, the covartiates are defined based on each single model specification (see Table 1.4). *Age*, *Households size* and *Children* are continuous variable for age of the survey respondent and the number of household members and the number of children in the household, respectively. The covariate *Woman* is a dummy variable for gender that takes value zero for male and one for female. The covariates *Medium education* and *High education* capture the effect of education attainment and are dichotomous indicator variables for secondary level and tertiary level of education. The variables *Medium urbanization* and *High urbanization* capture if the respondent was resident in small urban areas (i.e. 100 - 499 inhab/sqkm) or in large urban areas (i.e. >= 500 inhab/sqkm) against the base group living in rural areas (i.e. < 100 inhab/sqkm). The dummy variable *Owner* captures the ownership status of the respondent and takes value 1 if the respondent is the landlord, 0 otherwise. Finally, the variable *Financial situation (FS)*, captures the households perceived satisfaction with its financial situation that varies from "Not Easy at All", for the most vulnerable households, to "Very Easy", for the most affluent households.

Table 1.4 reports the estimation results for six different models [5]. We refer to these models as EM-FM, respectively. In particular, models EM relate to the specification with EM_k as dependent variable, and models FM refer to the logit models that have FM_k as dependent variable. The technology under consideration is reported in the second row of Table 1.4. The estimation results allow us to compare the probability of adoption of the k respondent with the profile in base line

[4] Stepwise regression through a backward variables selection.

[5] Note the estimation results in Table 1.4 refer to the model with the subsample of households that reported either financial or environmental concerns, estimation results for the subsample of households that reported environmental and financial concerns are not reported, but available on request.

model where a low income (low education attainment) tenant male respondent living in rural areas with little or no concern in the i matter is considered, controlling fro country effects [6].

[6]Country-level regressions are weighted by the share of socio-demographic groups in the population of each country. *** significant at 99%; ** significant at 95%; *significant at 90%

Table 1.4:

	Dependent variable:					
	EM (Light)	FM (Light)	EM (Appl)	FM (Appl)	EM (Ins)	FM (Ins)
Age	0.012***		0.011***		0.019***	
	(0.003)		(0.003)		(0.005)	
Woman	0.450***	0.315***	0.514***	0.331***	0.736***	0.592***
	(0.070)	(0.087)	(0.074)	(0.093)	(0.128)	(0.147)
Medium education	0.352***	−0.016	0.425***		0.539***	−0.459**
	(0.096)	(0.128)	(0.102)		(0.182)	(0.221)
High education	0.699***	0.266**	0.737***		0.427**	0.162
	(0.106)	(0.136)	(0.112)		(0.193)	(0.242)
Medium urbanization		0.125		−0.087	0.150	0.170
		(0.118)		(0.126)	(0.157)	(0.206)
High urbanization		−0.186*		−0.258**	0.382**	−0.375**
		(0.108)		(0.117)	(0.153)	(0.179)
Owner	0.130*	−0.293***	0.173**	−0.256**		
	(0.078)	(0.102)	(0.082)	(0.108)		
Not easy FS	0.356***	0.144	0.522***	0.328	0.914***	0.453
	(0.115)	(0.217)	(0.120)	(0.229)	(0.198)	(0.319)
Fairly easy FS	0.477***	−1.047***	0.593***	−0.948***	1.181***	−0.675**
	(0.119)	(0.204)	(0.124)	(0.212)	(0.207)	(0.295)
Very easy FS	−0.062	−2.249***	0.173	−2.167***	0.630***	−1.969***
	(0.141)	(0.214)	(0.149)	(0.222)	(0.234)	(0.308)
Household size	0.087***		0.058*		0.246***	
	(0.032)		(0.034)		(0.060)	
Children		0.116**		0.135**		
		(0.050)		(0.054)		
BELGIUM	0.059	−0.640*	0.088	−0.421	0.321	−0.504
	(0.373)	(0.369)	(0.378)	(0.366)	(0.667)	(0.714)

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Table 1.4: (Continued)

BULGARIA	−0.133	−0.339	−0.057	−0.068	0.156	−0.412
	(0.360)	(0.404)	(0.363)	(0.409)	(0.581)	(0.695)
CROATIA	0.149	0.787	0.023	0.624	−0.034	1.129
	(0.452)	(0.630)	(0.439)	(0.595)	(0.697)	(1.214)
CYPRUS	2.086	3.425	1.842	3.437	2.755	2.804
	(1.643)	(3.183)	(1.553)	(3.183)	(4.506)	(4.542)
CZECH REPUBLIC	−0.771**	0.381	−0.830**	0.289	−0.767	0.104
	(0.314)	(0.410)	(0.325)	(0.429)	(0.534)	(0.713)
DENMARK	−0.281	−0.404	−0.508	−0.333	−0.288	−0.432
	(0.412)	(0.407)	(0.414)	(0.413)	(0.659)	(0.723)
ESTONIA	−0.663	−0.450	−0.692	−0.397	−0.682	−0.864
	(0.600)	(0.757)	(0.615)	(0.798)	(1.079)	(1.248)
FINLAND	−0.589	−0.276	−0.633	−0.230	−0.648	−0.260
	(0.405)	(0.444)	(0.415)	(0.449)	(0.773)	(0.895)
FRANCE	−0.074	−0.709**	0.001	−0.566*	0.915*	−0.554
	(0.280)	(0.309)	(0.278)	(0.302)	(0.528)	(0.614)
GERMANY	−0.328	−0.193	−0.381	−0.098	−0.411	−0.306
	(0.272)	(0.304)	(0.269)	(0.295)	(0.487)	(0.613)
GREECE	1.222***	1.704***	1.100***	2.098***	1.632**	0.942
	(0.409)	(0.581)	(0.415)	(0.696)	(0.793)	(0.911)
HUNGARY	1.623***	0.909*	1.655***	1.291**	1.995**	1.234
	(0.468)	(0.493)	(0.478)	(0.567)	(0.874)	(1.054)
IRELAND	0.080	0.790	−0.164	0.809	−0.062	0.698
	(0.469)	(0.664)	(0.476)	(0.695)	(0.766)	(1.253)
ITALY	1.442***	1.004***	1.373***	0.911***	1.382**	0.607
	(0.309)	(0.331)	(0.309)	(0.323)	(0.562)	(0.648)
LATVIA	−1.361***	−0.450	−1.393***	−0.442	−1.472*	−0.374
	(0.448)	(0.631)	(0.453)	(0.644)	(0.794)	(1.134)
LITHUANIA	−0.433	0.571	−0.408	0.610	−0.075	0.323
	(0.461)	(0.679)	(0.475)	(0.687)	(0.842)	(1.105)
LUXEMBOURG	0.459	−0.480	0.598	−0.460	1.708	0.188
	(1.339)	(0.999)	(1.476)	(1.031)	(3.680)	(2.231)
MALTA	2.083	4.613	1.977	4.575	2.234	3.538
	(2.169)	(6.620)	(2.171)	(6.634)	(4.229)	(6.736)

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Table 1.4: (Continued)

NORWAY	-1.114^{***}	-0.819^{*}	-1.246^{***}	-0.584	-1.077	-1.008
	(0.404)	(0.447)	(0.407)	(0.465)	(0.754)	(0.849)
POLAND	-0.670^{**}	0.063	-0.602^{**}	0.208	-0.744	-0.043
	(0.285)	(0.333)	(0.296)	(0.354)	(0.520)	(0.669)
PORTUGAL	0.660^{*}	2.429^{***}	0.733^{**}	2.366^{***}	1.512^{*}	14.800
	(0.360)	(0.774)	(0.369)	(0.770)	(0.822)	(387.716)
ROMANIA	-0.119	0.170	-0.150	0.062	-0.029	-0.386
	(0.293)	(0.341)	(0.293)	(0.334)	(0.537)	(0.654)
SLOVAKIA	0.527	1.021	0.641	0.981	0.060	1.910
	(0.651)	(0.866)	(0.781)	(0.945)	(1.165)	(2.508)
SLOVENIA	0.300	1.374^{**}	0.345	1.390^{**}	-0.113	1.331
	(0.416)	(0.582)	(0.464)	(0.655)	(0.651)	(1.051)
SPAIN	-0.166	0.758^{**}	-0.071	1.036^{***}	2.519^{***}	1.050
	(0.280)	(0.340)	(0.284)	(0.352)	(0.952)	(0.780)
SWEDEN	-0.520	-0.908^{**}	-0.662^{*}	-0.664^{*}	-0.602	-0.790
	(0.365)	(0.378)	(0.374)	(0.391)	(0.713)	(0.755)
THE NETHERLANDS	-0.043	-0.399	-0.009	-0.526	-0.283	-0.558
	(0.341)	(0.357)	(0.347)	(0.348)	(0.541)	(0.646)
UK	-0.640^{**}	0.798^{**}	-0.732^{***}	0.750^{**}	-0.703	0.546
	(0.274)	(0.329)	(0.271)	(0.315)	(0.486)	(0.625)
Constant	0.222	3.044^{***}	0.140	3.056^{***}	-1.286^{**}	2.935^{***}
	(0.333)	(0.370)	(0.337)	(0.358)	(0.612)	(0.669)

Looking at Table 1.4 it appears that gender is an important determinant since the estimated coefficients for *Woman* are significant no matter the cost of the technology nor the concern under consideration. With respect to the empirical literature studying environmental concern, previous studies suggest that women express greater concern for the environment than man (Hunter et al., 2004), while this is against the evidence supported by Shen and Saijo (2008). Being older slightly increase the probability of adoption for environmentally concerned households, no matter the cost of the technology under consideration, whereas *Age* is not significant in the models analysing the socio-demographic characteristics of financially concerned households. This does not supports the view expressed in Trotta (2018) that older households may have higher expected returns from the adoption of energy savings technologies. Moreover, the majority of previous studies report that age is negatively correlated with the environmental concern measures they applied (Mills and Schleich, 2012), while, in line with Shen and Saijo (2008), age is estimated with significantly positive sign in all the three technologies.

Interestingly, the parameter estimates suggest education has a strong impact on household energy conservation only for those adopting for environmental reasons, indicating that medium and high education groups are more environmentally concerned than those without college degrees. This result is consistent with most previous studies (Mills and Schleich, 2012; Shen and Saijo, 2008). The same in not true for financially concerned households where the covariates for education are significant for thermal insulation only but with a negative effect.

Living in large urban areas increases the probability to adopt high cost technologies for environmentally concerned respondents. Similar results are found in Kastner and Stern (2015) where a positive correlation between population density and energy efficiency investments was found. The same is not true for financially minded households as the estimated parameters for *High urbanization* are negatively correlated to energy saving investment due to financial reasons.

The effect of ownership is studied only for lights and appliances [7], as the adoption of high cost technologies, such as insulation measures, is generally related to the split-incentive problems, with landlords that tends to under invest in energy efficiency measures when is the tenant who pays the electricity bills (Melvin, 2018; Castellazzi et al., 2017). Results shows that ownership decreases the likelihood of adoption of financially minded households, while the opposite occurs for adopters that are highly concern about environmental issues, but with a less strong effect.

The effect of the households financial situations show interesting results when comparing environmentally and financially minded households. For the former, the positive and significant coefficients tends to decrease with increasingly easy financial situation. Therefore, suggesting that households financial situation plays a positive role for environmental concern up to a certain point. The positive effect of income on environmental concern is supported also by the findings of Shen and Saijo (2008). On the other hand, for financially minded individuals, an increase in their economic resources negatively affects the likelihood of adoption for all the considered technologies. This result suggests that, for the most affluent households, the cost saving of energy efficient technologies impact less on their economic resources and therefore is a less considered aspects. This is particularly evident looking at the coefficient estimate for thermal insulation, which has the higher negative effect.

Looking at the results for *Households Size* it appears that the estimated coefficients are positive and significant in all estimated models for environmentally concerned households, thus supporting the results in Urban and Ščasnỳ (2012). It is interesting to note that the estimated coefficient is greater in magnitude in the model analyzing insulation, suggesting that higher impacting investment in terms of environmental benefits are deemed more important in larger families.

The presence of children (under 16 years old) is significant in increasing the model reliability only for the households investing in energy saving due to cost reduction reasons. However, the estimated coefficient are positive and significant only for light and appliances adopters.

1.6 Conclusion and Policy Implications

Policy makers in the EU have set binding targets of energy efficiency [8] that pivot on several actions including reducing energy consumption for households and businesses as well as improving energy

[7] The regression model for *Insulation* is studies on the subset of home owners

[8] At least 32.5% by 2030, relative to a ‘business as usual’ scenario. ((EU) 2018/2002, (EU) 2018/844).

performance in buildings. In spite of the implementation of the energy efficiency legislation and ambitious energy efficiency programmes in Europe, empirical evidence shows that energy consumption is still above the targets (see for example the report on Energy, Transport and Environmental Statistics, 2019). Against this background, we study the households' adoption of energy efficient technologies using a large dataset of thirty European countries in relation to their environmental and financial concerns. We corroborate the evidence that households' decision of adopting energy efficient technologies is not exclusively based on rational cost-benefit analysis by showing that non-economic factors such as environmental concerns also drive adoption behaviour.

Using stochastic dominance methodology we show that adopting households that are highly concerned in environmental or/and financial matters adopt more energy efficient technologies than their counterpart with low (or no) concerns, no matter the cost of the technology under consideration (Proposition 1 and 4). However, the stochastic dominance analysis results suggest that economic factors mitigate the effect of environmental and financial attitudes on the adoption behaviour, supporting the attitude-action gap hypotheses (see also Corraliza and Berenguer (2000); Melvin (2018); Trotta (2018)). A statement of "high concern" in environmental matters translates to action only for low-to-middle cost technologies (low-energy bulbs and energy efficient appliances, respectively), but not for costly thermal insulation technology (Proposition 3). Similarly, the comparison between environmental and financially concerned households shows that environmental concern is a stronger determinant than financial concern for low-medium cost technologies, while financially concerned households adopts more high cost technologies compared to environmental concerned households (Proposition 5). Conversely, low motivation toward environmental or financial matters leads households to act accordingly and not to invest in expensive insulation technologies (Corollary 1 and 2).

Looking at the socio-economic profiles of different households it is found that environmentally minded and financially concerned households who have adopted energy-saving technologies feature rather different socioeconomic background: educated households with medium-high financial resources and large families are more likely to be environmental concerned whereas household in difficult financial situations and with children are more likely to be financially concerned.

Our results show that, in addition to traditional measures aiming at financing building energy renovation and at subsidising the purchase of energy efficient appliances, actions that increase financial and environmental awareness (see, for instance, the Intelligent Energy – Europe (IEE) action) directly contribute to achieve greater levels of adoption. Information campaigns are low cost policy instruments that do not require the deployment of financial tools and impose low bureaucratic burden on citizens and institutions. In this respect our results suggest that information measures to promote reduction in energy consumption across EU Member States may be used to support more expensive policy tools such as subsidies, loans and tax incentives. In this respect, our findings may be relevant to inform policy setters looking for feasible ways to foster the adoption of energy saving technologies. Moreover, by separating the behaviour of environmentally and financially concerned households we can explore the different effect of the value-action gap across technologies and subjects. In the same line, our estimates delineate a profile of environmentally and financially households helping in identifying the most appropriate recipients of specific policy measures.

Chapter 2

The role of economic, behavioral and social factors in technology adoption.

Giulia Chersoni, Nives Della Valle, Magda Fontana

Abstract

The paper models the choice of adopting a technology as a combination of economic, behavioral, and social factors and discusses their relative role in the diffusion of the technology. The model encompasses the cost of the technology, the propensity to adopt and the imitative behavior. Results show that the traditional adoption curve only emerges when the decision to adopt a technology is driven uniquely by imitation. It also appears that the rate and level of diffusion depend on the structure of interaction - i.e. network topology -. Interestingly, if agents interact in preferential attachment environments, the adoption is higher than in small world topologies when we take into account economic, behavioral, and social factors. Overall, the paper suggests that none of the considered elements taken in isolation can explain the adoption decision.

2.1 Introduction

Understanding the drivers of technology adoption is a key topic in economics. Research follows three main lines: traditional models depict technological choices as based on the comparison between monetary costs and benefits (Rivers and Jaccard, 2006; Mundaca et al., 2010). The behavioral economic literature suggests that the decision to adopt a technology can also be influenced by behavioral factors (Bendell, 2017; Newell and Siikamäki, 2015; Qiu et al., 2014). Finally, epidemic models stress the role of imitation in technology adoption (Griliches, 1957; Beretta et al., 2018).

In this paper, we show that the three approaches are not mutually exclusive and we highlight the marginal effect of each of them on the level and pace of adoption. Conventional bottom-up models characterize technological choices in terms of capital and operational costs, and their profitability in the long-run based on their discounted value (Rivers and Jaccard, 2006). However, part of the relevant literature (see for example Mundaca et al. (2010)) emphasizes that such models only account for purely economic motives. At the same time, they oversimplify decision-making by assuming complete information, homogeneity of agents, and no interaction among them. Conversely, the field of behavioral economics enables to account for the cognitive limitations that bias the decision-making process and to acknowledge individual heterogeneity not only in terms of what individuals prefer, but also in terms of how much they differ in their degree of self-interest and motivations. Finally, epidemic models consider diffusion as a social contagion process based on imitation but, in most cases, do not thoroughly assess economic motives and cognitive biases (Geroski, 2000).

We claim that adoption is affected by all these three elements and that their relative role has not been examined so far. To investigate this issue, we join the three parts in an agent-based model (ABM) that accounts for heterogeneity (in a behavioral perspective) and decentralized interaction (as in epidemic models). We start from the framework devised by Bénabou and Tirole Bénabou and Tirole (2011b) in which individual decisions concerning public goods are influenced by economic and behavioral factors, and by peer pressure, and we reframe the model in order to make it applicable to private goods. In their model, decisions are made by balancing inner motivations (i.e. the degree of other-regarding concerns) and social influence (i.e. reputational costs and benefits). We translate the former into a general agent's propensity to adopt – that intuitively varies across individuals –, and the latter into neighbors' influence. It is worth noting that peer pressure *à la Bénabou and Tirole* (Bénabou and Tirole, 2011b) assigns the same weight to all the signals, whereas in epidemic models and in our ABM, agents weight the information on the basis of their individual characteristics, i.e. their propensity to adopt. Agents with weak inner motivations (i.e. low propensity to adopt) are more likely to conform to the behavior of others (i.e. have a high propensity to imitate) (Bénabou and Tirole, 2011a).

It is widely acknowledged (Beretta et al., 2018; Schilling and Phelps, 2007; Singh, 2005) that the structure of the neighborhood affects the level and the pace of innovation diffusion. In our ABM agents with heterogeneous propensity to adopt interact in different network topologies (small world and preferential attachment) and make decisions on the basis of the information gathered in their neighborhood as in traditional epidemic models (Griliches, 1957). Overall, the decision has three drivers: the economic factors (income and investment cost), the behavioral component (propensity to adopt), and the sensitivity to neighbors' influence (propensity to imitate) mediated by the network topology.

Results show that the traditional adoption curve only emerges when the decision is driven uniquely by neighbor's influence. Whereas, when we consider economic and behavioral elements we obtain diverse and interesting adoption paths. This implies that studying adoption from a single perspective neglects relevant aspects of both the decision-making and the diffusion process.

The paper is organized as follows: section 2.2 illustrates the literature that is relevant for the analysis, section 2.3 illustrates the model and the research questions, section 2.4 presents the results, and section 2.5 discusses and concludes.

2.2 Theoretical Background

According to the literature, the decision to adopt a technology can be affected by three main elements: economic, behavioral and social factors. Economic factors consist in the cost and benefits associated to the technology and in the potential adopter's income constraints. Behavioral economics, while highlighting that individuals are often incapable of performing optimal decisions, suggests that the outcome of the comparison of cost and benefits is distorted by the presence of systematic cognitive biases. Individuals might assign to the benefits delayed in the future a weight that is lower than that assigned to the present purchasing cost (*present bias*) (Newell and Siikamäki, 2015) and can be loss averse (*framing effect*)(Tversky and Kahneman, 1992). Also, individuals care not only about their own well-being, but also about that of others (Cooper and Kagel, 2016): *other-regarding concerns* might enter the decision to adopt a technology if it also entails public benefits (Orsato, 2006). Finally, social factors such as peer pressure are investigated in the literature on innovation through the so- called epidemic models (Geroski, 2000) where a technology spread as a social contagion fostered by imitation (Rogers, 2010).

In this study, we propose a model that can account for all the three factors by amending the model by Bénabou and Tirole (2011b). As will illustrated in the following section, we change their original model to include the propensity to adopt (instead of other-regarding behavior) and we apply it to a private good (instead of a public good).

The model is not analytically solved but, in order to encompass individual heterogeneity, is simulated via an agent-based model (Rahmandad and Sterman, 2008; Kiesling et al., 2012). We relax the homogeneity and perfect mixing assumptions (Griliches, 1957) of epidemic models and we introduce local network effects (Valente, 1996). In our model, the increase in the proportion of adopters affects individual decision depending on the structure of the individual's network. Namely, *ceteris paribus*, the decision of adopting a technology is made when a certain threshold of adopters is reached within the individual neighborhood [1].

2.3 The model

The model describes the adoption decision made by a heterogeneous population of agents interacting on a network.

The decision rule of agent *i* is the following:

$$Adoption(i,t) = \begin{cases} 1, & if \ \ Z < ((1-\beta)/2)EB + \beta N \\ 0, & otherwise \end{cases} \tag{2.1}$$

where EB represents economic and behavioral factors, N is the neighborhood (i.e. social) influence, and β ($0 \leq \beta \leq 1$) is their respective weight. If $EB = 0$ the net effect of economic and behavioral factors cancels out and the investment choice depends only on N, while when the cost

[1] Differently from Valente (1996), in our model the threshold variable is an individual feature, rather than of the network

of the investment is too high relative to the agent's income, the economic factor takes over the positive effects of propensity to adopt ($EB < 0$). Finally, when $EB > 0$ and $\beta < 1$, adoption is positively affected by economic, behavioral, and neighbors' decisions.

In particular,

$$EB = (v_i - c_i) \tag{2.2}$$

where the agent propensity to adopt is measured by the parameter v_i ($0 \leq v \leq 1$) and the financial burden associated to the investment is measured by the parameter c_i ($0 \leq c \leq 1$). The latter is the normalized ratio between the cost of purchasing the technology and the agent's income. If y_i is the agent's income and $m_i = 1/y_i$ is the relative cost of the investment, $c_i = (m_i - m_{min})/(m_{max} - m_{min})$, with $0 \leq c \leq 1$, is the normalized relative cost. Therefore, higher y_i corresponds to lower m_i and, consequently, to a lower financial burden: agents with high income level and low financial burden have c_i that approximates 0. Similarly, $EB < 0$ when the propensity to adopt is low or the cost of investment is high with respect to the agent's income.

Finally, N is formalized as follows:

$$N = \frac{n_{adopt,i} + (n_{adopt,j} * q_i)}{n_{i,j}} \tag{2.3}$$

where n_i is the number of neighbors with a similar level of propensity to adopt, n_j is the sum of the remaining neighbors[2], and q_i ($0 \leq q \leq 1$) is the propensity to imitate, which is inversely proportional to v_i. The idea underlying this assumption is that individuals with weak inner motivations (i.e. low propensity to adopt) are more likely to conform to the behavior of others, in comparison with those who have high prior on their inner motivations (Bénabou and Tirole, 2011a). The likelihood to adopt increases as N increases, i.e. as the number of adopters in the agent neighborhood network increases (the numerator of Eq. 2.3). This effect is stronger for those agents with a high propensity to imitate (higher q_i).

The structure of the neighborhood is modelled by resorting to three typical network topologies: a small-world network with high and low clustering (Watts and Strogatz, 1998), and preferential attachment(Barabási and Albert, 1999). Small world networks reflect the propensity to create tighter and more numerous relationships with individuals that are close in terms of a given dimension[3]. The high number of cliques assures that if a links drops out, the relationship between the remaining individuals does not suffer from fragmentation, and the nucleus remains intact (Granovetter, 1978). Preferential attachment networks [4], on the other hand, approximate social interactions mediated by a leader (i.e. node with higher degree). In social environments with preferential attachment structure, the diffusion process is mediated by a subset of central nodes, while diffusion in small world societies results from more decentralized interactions. As for the pace of adoption, the literature agrees that small world networks accelerate diffusion with respect to preferential attachment networks(Beretta et al., 2018).

Finally, Z is a stochastic process that encompasses all the elements that are assumed to affect

[2]Two agents are considered similar if their propensity to adopt differs less than ± 0.2. For a similar approach see Beretta et al. (2018).

[3]The network has been generated with the Kleinberg algorithm

[4]The network has been generated with the Barabasi-Albert algorithm

Table 2.1: Simulation scenarios

Variable	Range of values
β	0.0 - 1.0
c_i	0.0 - 1.0
v_i	0.0 - 1.0
Share of agents with low income ($y_i < \tilde{y}$*)	0, 25, 50, 75
Share of agents with low propensity ($v_i < \tilde{v}$*)	0, 25, 50, 75
Networks	Preferential attachment, Small world
First adopter	Marginal, Betweenness, Eigenvector
QI	$\beta(0,1)$, $v_i(0,1)$, $c_i(0,1)$
QII	$\beta(0,1)$, $v_i = 1$, $c_i(0,1)$
QIII	$\beta(0,1)$, $v_i(0,1)$, $c_i = 0$

*$\tilde{y} = 0.33$, *$\tilde{v} = 0.4$

adoption but are not explicitly included in the model. It assumes a uniformly distributed random value between 0 and 1. The population is heterogeneous since the value of v_i, c_i, and q_i are randomly drawn from a normal distribution.

We analyse the level and pace of adoption at the population level by focusing on the following questions:

Question I(QI): Assuming that the adoption is influenced both by EB and N, we ask which is their respective weight (β) in the adoption process.

Question II(QII): We also ask, for each level of β, how the population income (c_i) drives the adoption process.

Question III(QIII): Similarly, we inquire on the effect of the propensity to adopt (v_i).

2.4 Analysis and results

In order to answer the above mentioned questions, we simulate a population of 100 agents that are nodes of a network [5]. We observe the decision over a period of 100 steps after which the model stabilizes. For each scenario, we run 100 repetitions to account for stochasticity. In addition, we also control for the effect of the position of the first adopter on the network (e.g. its social relevance). We consider a marginal adopter chosen with a function that minimizes closeness centrality, and central adopters chosen with a function the maximise betweenness and eigenvector centrality [6]. The simulated scenarios are summarized in Table 2.1.

[5] We choose the number of agents in the population based on the theory (Wasserman and Faust, 1994) and evidence (Chen et al., 2012) that network size does not affect diffusion processes due to the fractal properties of networks.

[6] If there exists more than one agent with the same centrality values, then we randomize among them. We also simulated an adopter chosen randomly. Results, for each scenario, broadly correspond to the average output obtained from the marginal, betweenness and eigenvector adopters.

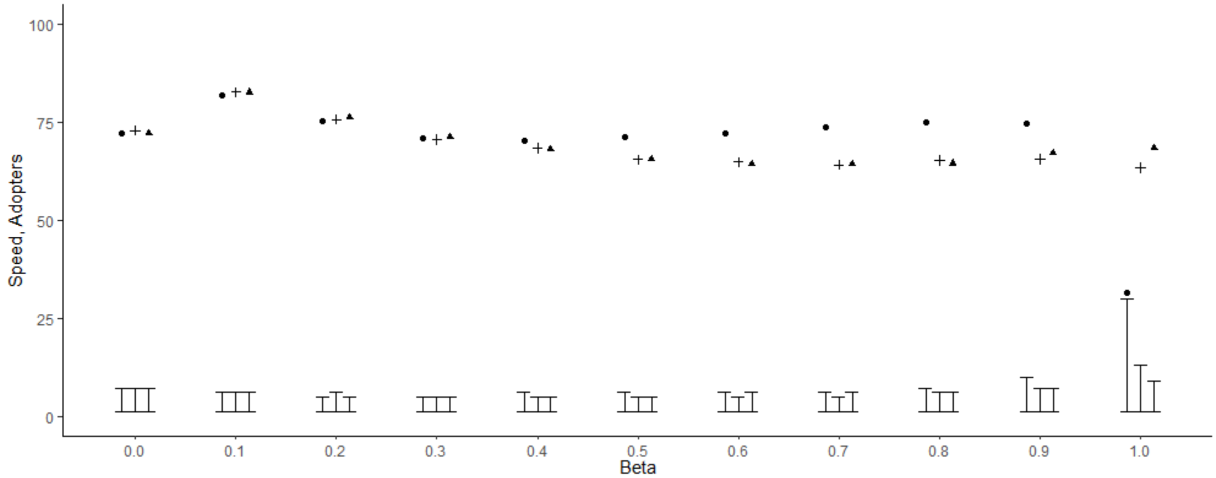


Figure 2.1: Simulation results for $\beta(0, 1)$ split by network type. Bars represents the diffusion speed by network topology: first bar preferential attachment, second bar small-world-high-cluster, third bar small-world-low-cluster. Points represent the mean number of adopters by network topology: circle preferential-attachment, plus small-world-high-cluster, triangle small-world-low-cluster. Simulation results with 10 % of agent with $c_i \leq \tilde{c}$ and $v_i \leq \tilde{v}$, and one first adopter.

2.4.1 QI: Balancing economic, behavioral and social motives

According to Equation 2.1, increasing the value of β results in an increasing weight of neighbors influence over economics and behavioral factors. Figure 2.1 [7] shows that the total level of adoption is almost unaffected for $0.0 \leq \beta \leq 0.9$ for all the networks. It also shows that, when $\beta = 1$, the adoption level is lower and the pace of diffusion is slower in preferential attachment topology. This depends on the hierarchical structure of the networks that limits redundancy of connections, therefore reducing the probability of having neighbors that have adopted.

For β equals to 1 we find a strong effect of the network type and of the position of the first adopter in the preferential attachment topology (see Figure 2.2). Unsurprisingly, when the first adopter is marginal, the level of adoption remains below the 25% of the population against the 50% of the central adopters. In the small world topology, the increase in β has a considerably less marked effect. The pace of adoption slightly slows down, but remains very similar to the results from lower values of β, while the difference across seeding method is not as sharp as in the the preferential attachment case. The different clustering in the small world networks does not heavily affect the results. In line with the literature, the high clustering generates a slightly lower level of adoption.

2.4.2 QII: Merging economic factors and neighbor pressure

To investigate the role of income, we simulate the adoption process with the maximum propensity to adopt ($v_i = 1$) and an increasing share of agents that cannot afford the technology. As expected,

[7] Figure 2.1 shows the diffusion speed defined as the number of iterations necessary to reach the inflection point of the adoption curve.

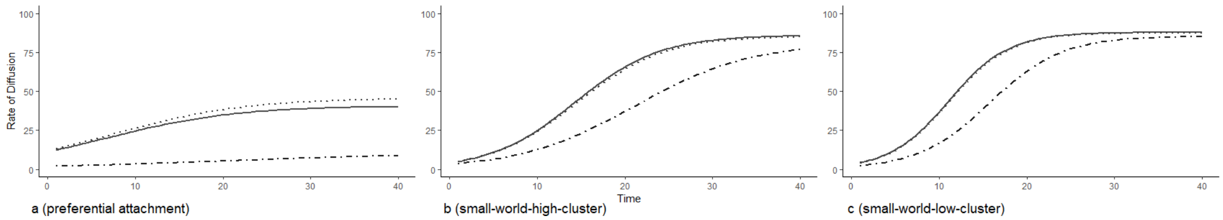


Figure 2.2: Simulation results for $\beta = 1$ split by type of network. Coloured lines represent the diffusion curves by the position of the first adopter in the network: dotted and solid line central first adopter (betweennes and eigenvector), dotdash line marginal position.

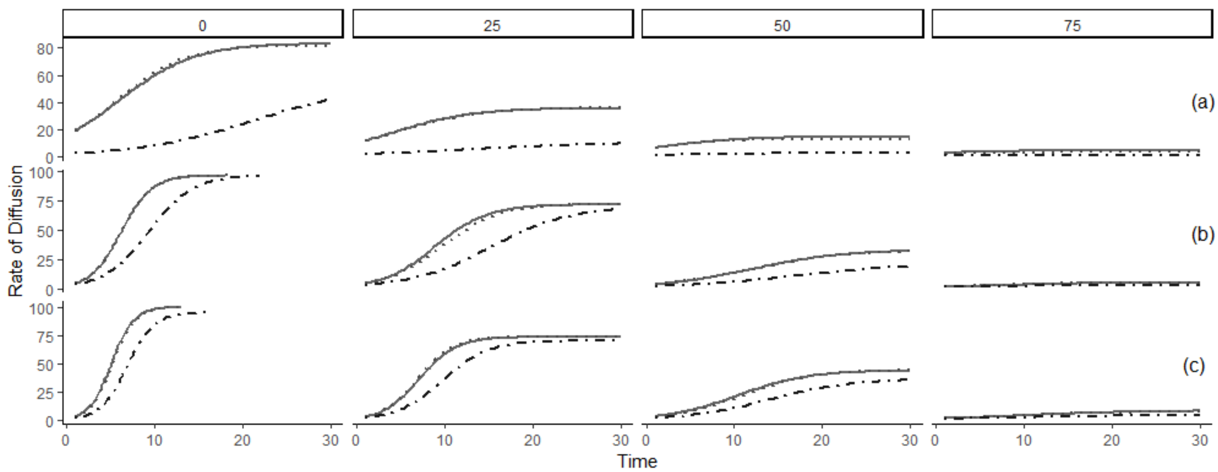


Figure 2.3: Simulation results for $\beta = 1$ split by type of network and share of agents with $c_i \leq \tilde{c}$. Coloured lines represent the diffusion curves by the position of the first adopter in the network: dotted and solid line central first adopter (betweennes and eigenvector), dotdash line marginal position. (a) preferential attachment topology with increasing share of agents that cannot afford the technology. (b) small-world-high-cluster topology with increasing share of agents that cannot afford the technology. (c) small-world-low-cluster topology with increasing share of agents that cannot afford the technology.

Figures 2.3 and 2.4 show that income positively affects the level of adoption. They also emphasize that, when the role of neighbors' influence is also accounted for, non-trivial results emerge.

Figure 2.3 reports the results of the simulation with $\beta = 1$. When all agents can afford and are willing to adopt, the diffusion is complete only for the small world topologies. While in the preferential attachment case, the role of N is stronger than the importance of EB. In addition, Figure 2.3 also confirms that the position of the first adopter in the network matters to the final level of adoption especially when the agent is marginal. On the contrary, there are no relevant differences between central first adopters. Furthermore, in the scenario where the 75% of agents have an income lower than the investment cost, all the network topologies slow down the diffusion process that remains below the potential 25%. This suggests the presence of a threshold of $c_i \leq \tilde{c}$, above which the dispersion of adopting agents on the network is too high to trigger the neighboring pressure.

Overall, Figure 2.4 highlights that the role of networks is not linearly increasing in the value of β. The process of adoption is almost unfettered by the presence of the network until $\beta = 1$. It

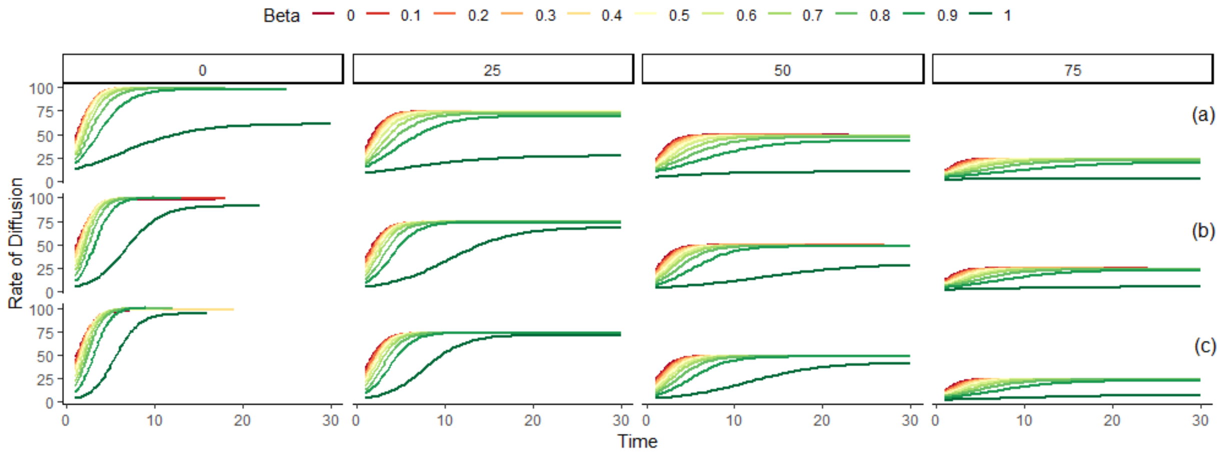


Figure 2.4: Simulation results split by type of network and share of agents with $c_i \leq \tilde{c}$. Coloured lines represent the diffusion curves by values of β. (a) preferential attachment topology with increasing share of agents that cannot afford the technology. (b) small-world-high-cluster topology with increasing share of agents that cannot afford the technology. (c) small-world-low-cluster topology with increasing share of agents that cannot afford the technology.

shows that the neighboring effect prevails only at the extreme of the parameter value. We can stress that epidemic models ($\beta = 1$) produce results that are very different from the more traditional EB perspective. This encourages further investigations, possibly empirical, on this matter.

2.4.3 QIII: The role of propensity to adopt

In the scenario QIII, we simulate the adoption process with no financial constraints ($c_i = 0$ for all agents) and with an increasing share of agents with propensity to adopt lower than the adoption threshold $v_i \leq \tilde{v}$. Recall that when an agent propensity to adopt is lower than the threshold, the adoption is possible only if more than 50% of its neighbors have adopted.

Figure 2.5 shows that even if the number of agents with $v_i \leq \tilde{v}$ increases and for values of $\beta > 0$, the neighboring effect described above pushes the adoption level over its potential level. The effect cancels out when we account for income (QII) and when we consider only EB ($\beta = 0$). Overall, the neighbor effect is stronger in small-world topologies. The differences among network topologies is more prominent in the 50% scenario, where the preferential attachment topology hinders diffusion and small-world topologies facilitate it. Among small-world networks, differences in diffusion speed are predominant in the 75% scenario. Low clustering coefficient eases information flows and speeds up diffusion rate also when $\beta = 1$, even if the effect takes longer to show (see Figure 2.5). Interestingly, in the latter case (when $\beta = 1$) the imitative effect is locked in the neighborhood of the first adopter and we observe a remarkable decrease in the pace and speed of diffusion. Neighbors' influence might hinder diffusion even more when there is homogeneity among neighboring individual. In particular, a higher v_i implies a lower q_i and therefore a lower imitative effect.

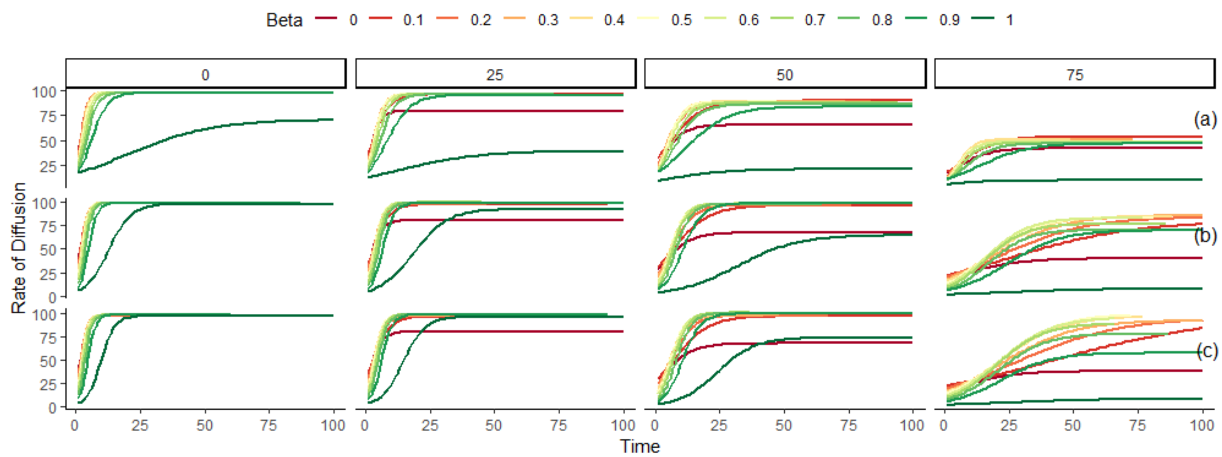


Figure 2.5: Simulation results split by type of network and share of agents with $v_i \leq \tilde{v}$. Coloured lines represent the diffusion curves by values of β. (a) preferential attachment topology with increasing share of agents with low propensity to adopt. (b) small-world-high-cluster topology with increasing share of agents with low propensity to adopt. (c) small-world-low-cluster topology with increasing share of agents with low propensity to adopt.

2.5 Discussion and Conclusions

The paper merges three approaches to depict the determinants of the adoption of technologies with the aim of appreciating their effect on the rate and total level of adoption. We have considered the traditional purely economic perspective together with the behavioral and epidemic approach. We have run an agent-based model to evaluate the relative role of three approaches and to assess the robustness of the findings that derive from each of them taken in isolation. The agent-based model provides interesting theoretical results that also have policy implications.

First, our results challenge the common finding that preferential attachment networks result in lower level of adoption and slower adoption processes. We find that this outcome only occurs when we assume that the adoption of a technology is uniquely determined by imitation. In all other cases, i.e. when behavioral and economic motives matter, the preferential attachment topology gives higher levels of adoption without any relevant delay in the speed of the diffusion process. This leads to reconsider the idea that small world networks are superior to preferential attachment in terms of diffusion. Overall, from a policy perspective, it seems that relying only on imitation to support adoption merely captures a fraction of potential adopters.

Second, in the same line, our model suggests that when the share of low-income population (e.g. with an income that does not allow to afford the technology) is above a certain threshold, the imitative driver is not enough to trigger widespread adoption. As demonstrated by Beretta et al. (2018), to overcome this issue, a policy intervention should target adopters on the basis of social or geographical proximity and increase their financial resources (e.g. general subsidy or proportional transfer by high-income neighbors to low-income neighbors). This would allow to reach the critical mass of adopters and, therefore, to foster diffusion.

Third, as opposed to the case of income constraints, the neighboring effect triggers diffusion above the share of agents that, according to their propensity to adopt, would not be willing to adopt. Based on this result, we claim that interventions that make the action of adopting more visible might be effective at increasing individual propensity to adopt by strengthening peer effects (Sacerdote, 2014; Wolske et al., 2020). Furthermore, when the initial threshold of individuals who engage in the desired behaviour is low (e.g. when imitation is locked-in the neighborhood of the first adopter), a norm-based intervention framed in a dynamic way (e.g., ‘more and more people are adopting the technology x’) might be effective at promoting adoption on a large-scale (Sparkman and Walton, 2017), with a probability of success that is higher the higher the degree of homogeneity of the target population (Bicchieri, 2016; Bicchieri and Dimant, 2019).

When dealing with actual populations, the assumption of acting on homogeneous groups is a strong limitation to the policy effectiveness. From this viewpoint, our model constitutes a test-bed for simulating the effect of such interventions in heterogeneous populations. At the same time, by pivoting only on a few variables (income, propensity to adopt and topology of interaction), our model unveils avenues for future research susceptible of empirical validation. Moreover, the modularity of the model also allows to simulate more diverse and sophisticated declinations of the behavioral (e.g. by including cognitive biases in the choice of adopting) and economic (e.g. by considering discounting effect) components.

Chapter 3

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

Giulia Chersoni, Nives Della Valle, Magda Fontana

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* (DG-Justice, 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 if economic, behavioural and social motives are accounted for then the effectiveness of the currently available policy portfolio needs considerable revising.

3.1 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 greenhouse gas emission reduction target to at least 55% compared to 1990 levels as part of the European Green Deal (EC, 2019b) 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 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 interaction[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

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

[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., 2019) for a detailed description of the theoretical framework.

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 3.2 reviews the relevant literature on energy efficiency adoption behaviour, Section 3.3 describes the theoretical model the setting and specifications of the agent-based model, section 3.4 illustrates the dataset, and section 3.5 presents the results of the policy simulation. Finally, section 3.6 puts results in perspective and discusses their policy implications, and section 3.7 concludes.

3.2 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, 1955). When making decisions under bounded rationality, they use shortcuts, i.e. heuristics (Tversky and Kahneman, 1974). That 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 et al., 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 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 Ščasnỳ, 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

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

[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

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 Ščasnỳ, 2012) and other high-cost technologies such as photovoltaic systems (Bashiri and Alizadeh, 2018a; Bergek and Mignon, 2017a). 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 neighbours are viewed as an important and trustworthy sources of information compared to expert advisors (Stieß and Dunkelberg, 2013; Filippini et al., 2020).

3.3 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.

3.3.1 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 et al., 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 choice 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

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).

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:

$$Adoption(i,t) = \begin{cases} 1, & if \;\; Z < [(1-\beta)/2]EB + \beta N \\ 0, & otherwise \end{cases} \tag{3.1}$$

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 and Eq. 3.2) and N is the importance of actor's *i* network of relationships in the choice to adopt (see Eq. 3.3). Finally, we introduce β ($0 \leq \beta \leq 1$) to test the hypothesis that adoption depends on the different motives and that they might have a different relative weight. It follows

[6]The full explanation of the re-interpretation can be found in Chen et al. (2012)

that if $\beta = 0$, then N has 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 normalised 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:

$$EB = (v_i - c_i) \tag{3.2}$$

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 modeled 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:

$$N = \frac{n_{adopt,i} * q_i}{n_i} \tag{3.3}$$

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 neighbours. Threshold models that account for personal network are more appropriate in the context where innovation is not directly observable, and it is perceived as uncertain and

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

risky (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").

3.3.2 The Agent-based model

The model presented in section 3.3.1 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. Neighbours 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 neighbours 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.

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

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).

3.4 Data

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

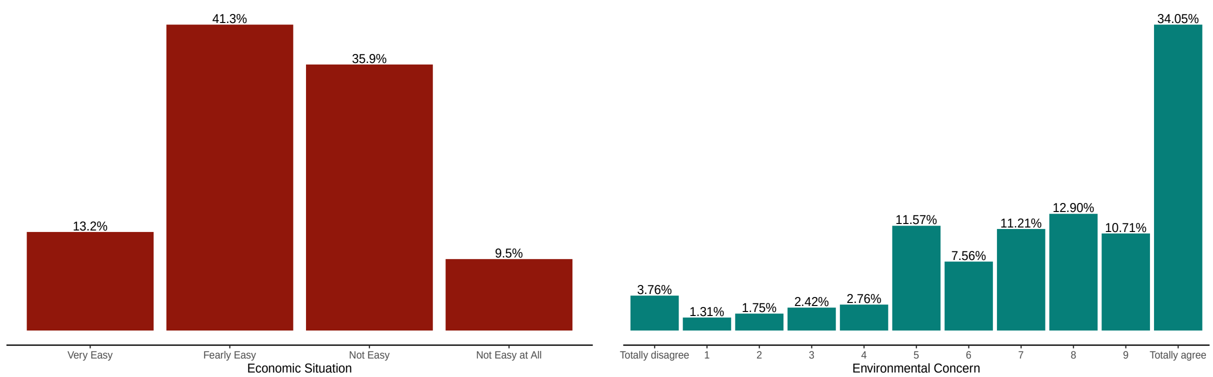
- Economic motives. *Survey question: Thinking about your household's financial situation, would you say that making ends meet every month is: Not easy at all, Not easy, Fairly easy, Very easy.*

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.

Figure 3.1 shows the distribution of economic and behavioural factors.



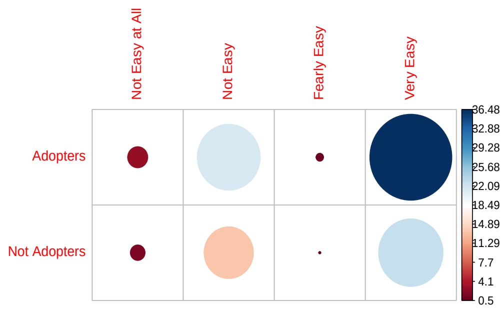
(a) Financial Situation

(b) Environmental Concern

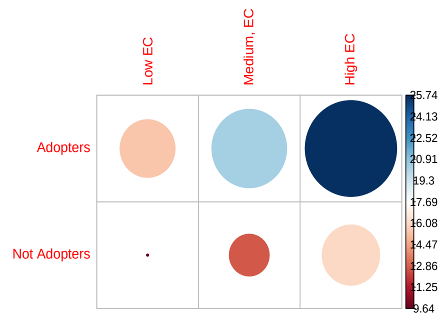
Figure 3.1: Relative frequency distributions of homeowners' perceived financial situation and level of environmental concern. Sample size 19,538. Source: Authors' calculation.

The income distribution is almost symmetric and concentrated around its medium values, while environmental 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

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 B). Figure 3.2 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").



(a) Financial Situation



(b) Environmental Concern

Figure 3.2: Correlation plots of the chi-squared test standardized residual. Figure 3.2a shows the correlation matrix between the homeowners perceived financial situation and the thermal insulation adoption. Figure 3.2b 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.

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 Figure 3.1) 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. 3.2), 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.

3.5 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.

3.5.1 Model behaviour

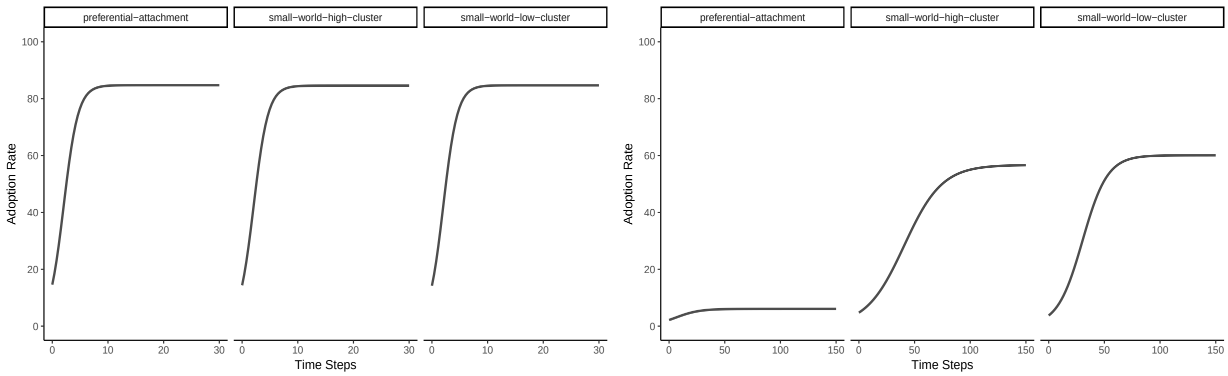
The general behaviour of the model has been explored in Chersoni et al. (2019). Here we briefly recall the main findings. The model shows that the role of the network is not linearly increasing with the value of β, and the imitation effect (i.e., N) prevails only for high values of β, with a more marked effect in preferential-attachment network. 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 characterised 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 $\beta = 1$ (Figure 3.3b). When agents behave in isolation instead, time is not relevant for adoption and the households that satisfy the economic and behavioural conditions adopt simultaneously (Figure 3.3a) [9]. 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 [10].

[9] For the complete results of the sensitivity analysis of the parameter β see Appendix C

[10] 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.



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

Figure 3.3: Figure 3.3a shows the adoption curve for $\beta = 0$ by network topologies. Figure 3.3b 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.

3.5.2 Policy simulations

We exploit agent-based modelling to analyse policy-making in both a prospective and a retrospective manner[11]. 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 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.

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 Sustainable Energy Authority of Ireland launched two initiatives: the *Better Energy Homes* [12],

[11]This classification is proposed and discussed at length by Hammond (2015) and Fontana and Guerzoni (forthoming).

[12]`https://www.seai.ie/publications/Homeowner-Application-Guide.pdf`

which funds 30% of the total investment cost of heating and insulation measures, and the *Better Energy Warmer Homes Scheme* [13], which specifically targets low-income homeowners offering free home energy upgrades. Similarly, the *Warmer Homes Scotland*[14] 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.

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 concerns. To appreciate the effect of this intervention, we increment the value of the parameter v_i for an increasing share of the population.

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

[13] https://www.citizensinformation.ie/en/housing/housing_grants_and_schemes/warmer_homes_scheme.html

[14] https://www.gov.scot/policies/home-energy-and-fuel-poverty/energy-saving-home-improvements/

the attractiveness of subsidies and the support programme for energy efficiency in the residential sector [15].

We account for the effect of trust and heterogeneity of roles by simulating a targeted norm-based intervention 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 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.

3.5.3 Policy simulation results

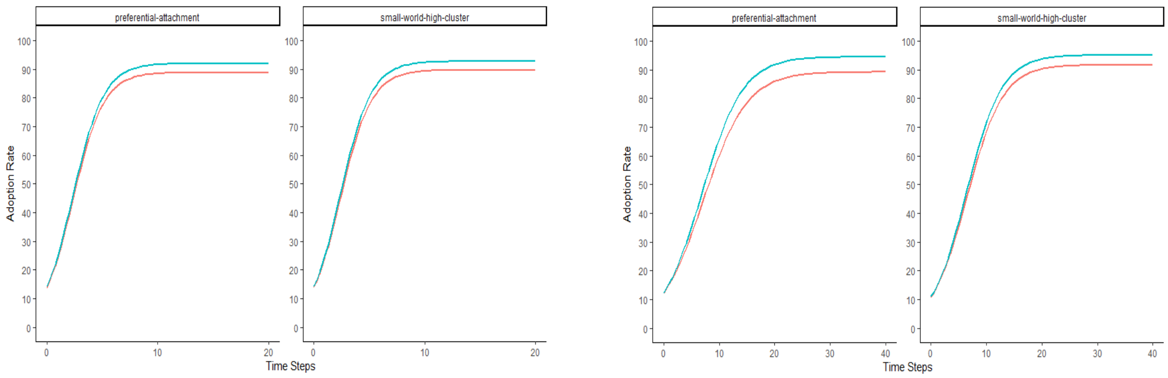
Far from being prescriptive, the results expounded in this section aim at showing that conceiving policies that lean on a broader framework can lead to a more thorough understanding of the adoption process and, consequently, to more effective policy interventions. In what follows, we describe how policy 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.

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

[15] `https://www.seai.ie/publications/Behavioural-insights-on-energy-efficiency-in-the-residential-sec` `pdf`



(a) $\beta = 0.2$ (b) $\beta = 0.8$

Figure 3.4: 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.

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 Figure 3.4)[16]. 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.

[16]The figures for all the policy interventions can be found in Appendix

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.

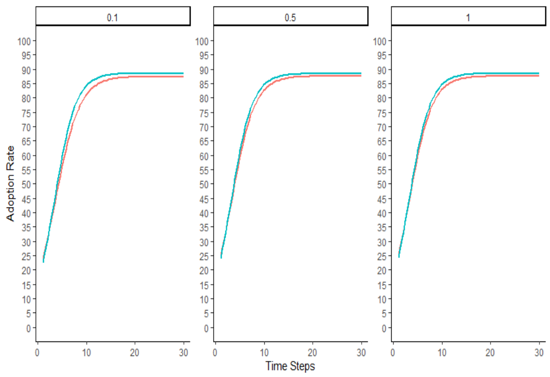
By construction a higher level of environmental concerns has two effects: first, it reduces the gap between v_i and c_i thus making adoption more likely; second, it makes individuals less sensitive to the behaviour of others, making imitation harder. We observe that the latter effect is neutralised in 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.

Social influence interventions

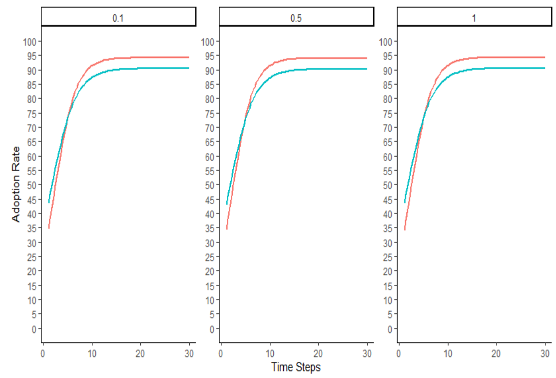
Modelled as a targeted-norm-based intervention where the most central nodes in the social network – the most trusted members of the community– are the first adopters. Yet again, the intervention is simulated for an increasing share of focal nodes (10%, 50%). With respect to the pro-environmental campaign, 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 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 Figure 3.5). 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 Figure 3.5a). However, the norm-based intervention proves to be more effective.



(a) Pro-environmental Campaign



(b) Norm-based Intervention

Figure 3.5: The figure shows the results of 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.

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.

3.6 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 technology 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, behavioral 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, forthoming). 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)[17]. 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 behaviourally 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 promoting 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[18].

[17]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.

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

3.7 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 concluding 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., 2019) 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 possibly, through the advancement of computational social science, by collecting more qualitative data on the households decision-making process.

Chapter 4

The establishment and viability of Renewable Energy Communities: An agent-based modeling framework

Giulia Chersoni

Abstract

The paper describes a conceptual agent-based model for the analysis of Renewable Energy Communities (RECs) establishment and viability under the Italian regulatory framework. The model seeks to explore the RECs initialization phase, i.e. households willingness to jointly finance local renewable energy production, and the RECs operational phase, i.e. households collective self-consumption patterns. Relying on the cooperative game theoretic approach, the process of coalition formation drives the collective adoption decision, while the marginal allocation rule shares RECs costs and benefits among the energy community members in a stable and fair way. The compensation mechanisms for self-consumption envisaged in the Italian regulatory framework is than simulated to analyze its effect on the profitability and long-term stability of the established RECs. The paper contributes to understand collective decision and their role on the transformation of the current energy system.

4.1 Introduction

The energy transition involves technological changes to move toward a carbon neutral society. Small-scale decentralized systems, where energy production and consumption are usually tightly coupled, are emerging as a viable alternative to the current centralized energy system, fostering innovative and responsible ways to produce, transport and store energy with the engagement of local communities (Bouffard and Kirschen, 2008). Indeed, the EU advocates a comprehensive energy transition, promoting renewable energy (RE) and entailing a more decentralised energy system with consumers becoming producers of the energy they consume, i.e. prosumers (EC, 2019b). The rationale behind incentivising energy prosumership is triggering private investments for the development of RE installations (Hanke and Lowitzsch, 2020). Empowering consumers and mobilizing new financial resources for renewable energy sources (RES), enables consumers to take responsibility of their energy consumption and production, increasing awareness of their energy usage and consumption habits (Dehler et al., 2017). Local energy systems can potentially contribute to the efficient energy production and distribution, helping meeting the climate objectives, and driving the energy system transformation form of bottom-up (Van Der Schoor and Scholtens, 2015; Van Der Schoor et al., 2016). This leads to shifts of decision-making from few concentrated and centralized production units to, among others, many micro and small decentralized generation units outside of the central unit's control (Hertig and Teufel, 2016).

Such a re-centralization of tasks to the collective level is experiencing growing academic and practical interest. The European Commission, though the Clean energy for all Europeans package introduced the concept of energy communities in its legislation, notably as citizen energy communities (CECs - EMI Directive (EC, 2019a)) and renewable energy communities (RECs - REDII Directive (EC, 2018)), as ways to 'organize' collective cooperation of an energy related activity around specific ownership, governance with a non-commercial purpose (as opposed to traditional market actors). The literature on energy community projects has extensively investigated the drivers that leads citizens to joint energy community projects (see for example (Bauwens, 2019; Koirala et al., 2018; Bauwens, 2016; Dóci and Vasileiadou, 2015; Bamberg et al., 2015). Only recently the literature has focused also on the viability of energy communities, i.e. on the way the value generated among its members is distributed (Tounquet et al., 2019; Abada et al., 2020; Moncecchi et al., 2020; Casalicchio et al., 2022).

The main drivers to join energy communities relate to environmental benefits (decrease in GHG emissions), financial gain (reduce energy bills), and willingness for energy independence (Agency, 2018; Brummer, 2018). In particular, presumption reduces the costs of energy consumption and provides an additional source of income though the sale of excess production to the grid. Indeed, empirical results highlight that the first individual motivations that drives the investment in renewable at community level is the expectation of economic gains in the long run through lower energy prices (Dóci and Vasileiadou, 2015). However, because by regulation no one can impose to a consumer to belong to an energy community, an unsatisfied group of members has always the choice to opt out from a community and consume electricity form the grid (EC, 2018). Since households participating in an energy community project can be very heterogeneous, the saving have to be allocated in a way that is considered acceptable enough by all members to stay in the community. Therefore, the satisfaction of a community depends on an equitable and fair allocation of the value created by the community members, as an inadequate allocation of the gains may jeopardize the stability of energy communities (Abada et al., 2020; Tounquet et al., 2019).

The value created by energy community members depends on the self-consumption patterns within the community and on whether excess production in a given period is remunerated. Self-consumption allow consumers to reduce the amount of the electricity they are billed proportionally to the energy they are able to generate and consume on site. On the other hand, the way in which the excess in production is remunerated can bring very diverse results in terms of the energy community profitability (Prol and Steininger, 2017). In that respect, the REDII Directive highlight that Member States need to ensure to prosumers a non-discriminatory access to support schemes for the electricity they feed into the grid ensuring that the system costs they are required to pay for electricity they feed into the grid are adequate and balanced (EC, 2018).This paper focuses on the effect of specific compensation tariffs design on the profitability of energy community projects. In particular, it focuses on Renewable Energy Communities and simulate Renewable Energy Communities (RECs) establishment in an Italian context, analyzing the gain stemming from the heterogeneous self-consumption patterns of its members, and the effect of the Italian self-consumption policies (GSE, 2020) on the RECs viability.

In order to do that, the present study rely on the agent-based modeling approach. The model aims to simulate RECs establishment as the macro level pattern emerging form simple micro-level interactions. Energy communities emergence is the result of households maximization behaviors, which based on their heterogeneous characteristics and interaction, might be able to collectively finance the joint RE investment. The model accounts for the social and economic aspects that motivate households to join a community energy project. Specifically, reproducing the model of Pasimeni and Ciarli (2018) it seeks to explore how social motives affects the network formation process though which households begun aware of the joint investment possibility and how the economic benefits stemming from joining a community energy initiatives influence the collective decision. In doing that, the formation of energy communities and the diffusion of renewable energy sources at the district level is explored. Once the REC is established, the model aims to examines whether the cost and benefit allocation among its member ensure the long term stability of the community. Namely, how the value the community produces, in terms of increased self-consumption and reduced electricity bills, is allocated among its members. The viability of RECs is also affected by the regulation in place. Therefore, the model will serve as the basis to test the effect of the compensation mechanisms established in the Italian context on the RECs profitability.

The study contributes to the existing literature in different ways. First, relying on dynamic network formation, it provides insights on the role of trust in the likelihood of establishing strong social interactions. Second, it extends the work of Pasimeni and Ciarli (2018)) modeling both the gains created by the community self-consumption patterns and the way these gains are shared within the community, therefore testing the RECs long-term stability (Abada et al., 2020; Tounquet et al., 2019). Third, it considers the effect of (self-consumption) compensation mechanisms on the value created by the community and therefore on its stability in the Italian context (GSE, 2020).

The work is organized as follow. Section 4.2 introduces the conceptual framework, i.e. the type of energy community projects modelled and the underlying assumptions. Section 4.3 explains the modeling approach, the theoretical background in which the agent-based model is embedded. Finally, Section 4.4 concludes.

4.2 Conceptual framework

The integration of increasing levels of distributed energy resources is a key challenge of future energy systems. Many integration options exists, such as virtual power plant, community micro-grid, and community energy systems. Each of these options differs in their objectives, for example, the aim of community micro-grids is to optimize electricity generation and demand for resiliency whereas virtual power plants aim at the management of aggregation and operation of distributed energy sources (Koirala et al., 2016). This study focuses on community energy systems, which refer to small and local energy systems for electricity (and or heat) production, governed by local people that invest and manage the local energy system (Walker, 2008; Walker and Simcock, 2012). These type of projects are implemented in a way that involves local populations and results in collective benefits for the local community (Walker and Devine-Wright, 2008). In particular, the type of community energy project that the present study aims to represent is that of a Renewable Energy Communities (RECs) as defined by the REDII directive (EC, 2018).

Following the underlying assumptions of the model with respect to the governance, ownership and activities carried out by the REC.

- *Technology*: Rooftop PV panels.

  The reasons to choice photovoltaics generation is twofold. First, it is the most common RES at the households level, due to space constrains within urban areas. Second, it represent the highest share of distributed power generation in the context of self-consumption of renewable energies.

- *Type of community*: Energy cooperative.

  Community energy systems may have a variety of organizational forms (Walker and Devine-Wright, 2008; Seyfang et al., 2013). The type of community energy project that the present study aims to represent is that of a Renewable Energy Community (REC) with a legal form of a cooperative. The cooperative organizational form is based on voluntary and open participation and on the democratic principle "one member, one vote" that offers limited liability and low financial barriers to entry. T. Local nonprofit energy cooperatives are specifically created to supply specific communities on the basis of self-consumption and sale of surpluses (Reis et al., 2021). The economic and social dimension of the cooperative business model make them particularly compatible with the multi-dimensional sustainability goals on renewable energy projects (Yildiz et al., 2015). Relying on collecting equity from their members, cooperatives are more likely to achieve member support and provide them with services.

- *Business model*: REC financed by its members contributions.

  The business model considered is that of a REC financed solely from its members' contributions (Lowitzsch and Hanke, 2019; Horstink et al., 2019). Community shares are the most common and cheapest financial instrument in the sector based on a review of business models and financial characteristics of energy community projects (Reis et al., 2021; Braunholtz-Speight et al., 2020). Analyzing the development of energy cooperatives in Germany and focusing on their financial characteristics, Yildiz et al. (2015) and colleagues have found that the shift towards higher capital rates, high membership numbers and stable equity ratio indicates that despite growing investment volumes financial requirements are still meet to a greater extent by members. Also at the European level, a recent study investigating 198 energy communities in nine MS, shows that a majority depends on their members equity contribution (Horstink et al., 2019). Under this simplifying assumption, individuals preferences to jointly invest and own RES, depends only on their electricity demand and on the individual contribution they are willing to commit to finance the investment.

- *Spatial dimension*: Urban district

  The model assumes that households are located in proximity to each other in a urban district area where they can decide to collectively finance the community-owned energy infrastructure. The concept of proximity is not well defined in the REDII directive and the proper definition and application is left to national laws. In the Italian regulatory framework [1] only members under the same secondary substation can constitute a REC (GSE, 2020), in Austria the division is performed at the grid level, and in France there is a differentiation between urban area (within 2 km) and rural area (within 20 km). To comply with the directive's proximity requirement the model refers to the usual definition of community of place (as distinct by community of interest), characterized by spatial closeness and high frequency of social interactions (Walker, 2011).

- *REC activities*: Energy generation, distribution, and collective self-consumption

  Once established, the REC acts as a combination of renewable energy producer and retailers (energy generation and distribution) connected to the electricity grid. The energy generated by the community owned PV plant is locally distributed and consumed by the member of the community (collective self-consumption). REC is connected to the electricity grid, therefore the community buys from the market the excess in demand and sell to the grid the excess in production, not having the possibility to store electricity. The study assumes that even if the electricity goes through the grid, PV production and consumption profiles are matched when self-consumption equal production profile in a given period. The level of self-consumption reduces demand from the grid ,avoids grid charges, and offers extra income to the community from the energy sold to the grid ensuring lower energy prices compared to grid retailers (Bauwens, 2016; Luthander et al., 2015)).

- *Grid tariffs*: Single connection point

  In compliance with the REDII Directive (EC, 2018), the REC is considered as a single connection point. It pays the network charges based on the general principles that apply to other consumers, therefore reducing the variable part of the network connection fees, as it counts as a single connection point.

- *Market tariffs*: Wholesale prices lower then retail prices

  When no incentives are offered to the excess of electricity production form the community owned PV system, it is more profitable for the community to increase the level of self-consumption reducing the amount of electricity bought form the grid (retail price), instead of selling the supply surplus (wholesale price).

4.3 Methods

The aim of the study is to simulate the establishment and successful management of energy community in the long run. In order to do so, agent-based models (ABMs) are a natural

[1]Law-decree 162/19 (articles 42bis)

and promising tool for improving the system understanding in order to explore under which circumstance RECs are more likely to emerge and endure (Edmonds, 2017). Other studies use the agent-based approach to investigate the factors leading to a successful establishment of energy community projects. Some look at the role of behavioural attitudes and leadership in community energy initiative (Ghorbani et al., 2020), others investigate the technical and institutional conditions (Fouladvand et al., 2022) or more trivial factors enabling thermal energy community formation (Fouladvand et al., 2020). The agent-based approach has been also extensively applied to study policy effectiveness in an energy transition context. ABMs have been developed to study the optimal mix of policy instrument to stimulate the diffusion of renewable energy technologies (Herrmann and Savin, 2017) or to test specific policies designed to enable a conflict-free energy system decentralization (Mittal et al., 2019). Fouladvand et al. (2022) simulate the role of subsidies and CO2 taxes effect on the development of thermal energy communities, and Pasimeni (2019) shows that policy instruments tailored to consumers' attitudes and specific subsidy schemes could encourage the shift to decentralized electricity systems in Italy.

4.3.1 Theoretical Framework

To model the establishment of RECs in a urban district the present study analyzes the social and economic factors that drive their development form an individual perspective. Following the work of Pasimeni and Ciarli (2018) the cooperative game theoretic approach (coalition formation theory) is used to model the emergence of collective actions stemming from individual choice, while network theory is use to model individual interaction and RECs diffusion. The model differs with respect to the literature on diffusion over network (see for example Valente (1996)) since it studies the diffusion process not as an individual adoption, but as a collective decision, conditioned by prior steps of coalition formation (Schlager, 1995). Moreover, it assumes that the network structure is not fixed but evolves over time allowing for the formation of new links spatially bounded. The collective adoption decision is modelled as a spontaneous and bottom-up process driven by heterogeneous agents with bounded rationality similar to the evolutionary model of firm formation of Axtell (2002). Evolutionary game theory permits to relax the common assumption of perfect rationality and homogeneity assumed in the game theoretic approaches, and model agents as heterogeneous in their preference and boundedly rational. Agents in the model are boundedly rational in that they don't evaluate all possible combinations of coalition, and based on their limited and incomplete knowledge select the optimal option maximizing their utility (Gigerenzer et al., 2001). Moreover, the social network structure affects agents behavior thought the evolution of links' connection between agents, which affects the collective decision to join the RECs.

The present study extends the model of Pasimeni and Ciarli (2018) analyzing the RECs inner functioning, namely how RECs, once established, share the benefits created by the community among their members. The establishment of the REC entails one source of costs, i.e. the cost of installation of the PV arrays, and two source of gains, i.e. the aggregation gains in the form of decrease network fees and the energy gains as the renewable energy can be consumed at zero marginal costs or re-injected into the grid providing additional income to the community. Those savings should be allocated in a way that any agents has an incentive to opt out from the community to ensure the RECs long-term stability. Again, the cooperative (coalition) game theoretic approach is used to analyze the costs and surplus sharing. Other studies have studied the ability of energy communities to adequately share the value created by the production and consumption patterns among the community members (Abada et al., 2020; Tounquet et al., 2019; Moncecchi et al., 2020; Casalicchio et al., 2022). In particular, based on the empirical evidence offered by Tounquet et al. (2019), the present study propose to analyze how the value created by the community is shared among its members, applying the marginal sharing rule. It finally extends the analysis studying how the incentive mechanism for self-consumption proposed in the Italian regulatory framework (GSE, 2020) affects the long-term viability of RECs.

4.3.2 The Agent-Based model

The agent-base model is articulated in the three typical components:

- *The agent*: the simulation has only one type of agent, the households. The households owns as their features their level of trust, their consumption profile and income. Each agent can have one of the following three states:
  - *eco-innovator*: the agent that propose the joint investment to its link neighbors.
  - *active*: the agent who knows about the investment opportunity and may decide to finance it.
  - *non-active*: members of the urban district that do not know about the community project.
- *The environment*: a network in which each households is represented as a node and links are the connections among households. Links convey the world of mouth information sharing about the REC investment possibility within an urban area.
- *The decision rule*: an utility function representing households preferences for the status-quo (buying electricity form a general provider) and the collective choice investment (willingness to contribute part of their income to finance the REC for production and self-consumption).

The model is divided in four main sub-models. The RECs establishment phase occurs under sub-model 1 and 2, while the assessment of RECs stability is studies under sub-model 3. Finally, sub-model 4 analyze the effect of the Italian compensation mechanisms for the part of the production not self-consumed by injected into the grid.

Sub-model 1: Network Formation

The process of REC establishment starts with the network formation process, with a random number of agents that act as initiators (eco-innovators) that propose the common investment to their link neighbors. The role of entrepreneurial individuals and their influence in mobilizing other actors has been proven significant (Bauwens, 2019; Sperling, 2017; Martiskainen, 2017; Hoffman and High-Pippert, 2010). Entrepreneurial individuals in the literature of innovation diffusion act as opinion leaders thought as trusted information source (Rogers, 2010). The role of social interaction in joining cooperative initiative is also supported by empirical evidence around energy community project determinants, where higher level of social interactions act as a strong drivers for investment at the community level (Bauwens, 2019). More generally, the importance of peer effect has been directly related to the diffusion of pro-environmental innovation (Bollinger and Gillingham, 2012).

Agents that act as eco-innovators are characterized by a high level of intrinsic motivation in committing time, money and effort into the project. In the dynamic process of network formation, new agents might become eco-innovators, and form new links, only when their level of intrinsic motivation reaches a minimum threshold. Eco-innovators contact randomly one of their neighboring agent and the contacted individual links with the eco-innovators if her level of trust in the community is positive . Trust is one of the social motivations driving people to invest in collective energy projects, it supports and enable cooperation, communication and commitment such that the energy community project can be developed in way that are consensual rather than divisive (Walker et al., 2010; Kalkbrenner and Roosen, 2016; Koirala et al., 2018; Yildiz et al., 2015; Warbroek et al., 2019). Similarly to the agent-based model developed by Ghorbani et al. (2020) trust within the community is incorporated in the model to build the social network of the agent: a higher the level of trust determines a denser network . However, in this study, network formation is not static but dynamic (as in Pasimeni and Ciarli (2018)): higher trust in the community increases the probability of forming new links, therefore the likelihood of creating actual connection in the network. Once contacted by an eco-innovators, if the trust condition is met, the contacted agents becomes active and can evaluate the joint investment.

Sub-model 2

The REC establishment phased is modelled following the work of Pasimeni and Ciarli (2018) as a sequential game of coalition formation, where agents autonomously negotiate in their social network to reach an agreement to jointly invest and finance the energy community project. In the sequential game of coalition formation, agents adapt their behavior and choices in relation to the evolving interaction with others (sub-model 1) and their preferences toward the common investment change over time with the attempt to form a coalition.

Once a network is established the eco-innovator proposes an investment to its connections, which cost depends on the PV capacity. The REDII directive does not impose any restriction to the size of RECs, leaving to each Member State to transpose the directive into national rules. The Italian legislation [2] imposes a maximum capacity size of 200 kW for energy community projects. Table 4.1 reports a re-elaborated sequence of PV systems sizes and associated unitary cost for small (10-100 kW) and large (100-250 kW) commercial building applied photovoltaic systems in Italy in 2020 (Tilli et al., 2020).

Agents decision to form or not a REC (i.e. coalition) depends on the evaluation of their utility. In order to form a REC agents have to commit part of their income to finance the PV investment, which depends to the monetary contribution others members decide to invest. The individual monetary contribution energy is the amount that maximize agents' utility in coalition. In the model

[2]Law-decree 162/19 (articles 42bis)

Table 4.1: PV system size and unitary price in Italy (Tilli et al., 2020)

System size [kW]	System price [€/kW]
10	1250
31	1217
52	1183
73	1150
94	1117
116	1083
137	1050

each agent evaluate its utility function for individualistic and collective consumption, modelled as Cobb-Douglas utility functions as follows (see Table 4.2 for the model initialization)

Utility function for individualistic consumption:

$$c_{i,1} = d_i(t)p_1 \tag{4.1}$$

$$U_{i,1} = (e_i - d_i(t)p_2)^{\theta}(d_i(t))^{(1-\theta)} \tag{4.2}$$

Utility function for collective consumption:

$$c_{i,2} = d_i(t)p_2 + x_i \tag{4.3}$$

$$U_{i,2} = (e_i - d_i(t)p_2 + x_i)^{\theta}(d_i(t) + D_i)[\frac{d_i(t)}{d_i(t) + D_{-i}} + \frac{x_i}{x_i + X_{-i}} + \frac{1}{N}]^{(1-\theta)} \tag{4.4}$$

Where $d_i(t)$ is the agents' i electricity demand (consumption profile), p_1 is the average electricity national price and p_2 is the average electricity price under collective consumption . The model assumes that $p_1 > p_2$ as renewable energy is consumed at zero marginal costs and the level of self-consumption reduces the amount of electricity demand from the national grid (self-consumed electricity is not subject to bills charges) and benefit form decreasing network fees. The parameter e_i represents agent's income, modelled following a lognormal distribution, while x_i is the proportion of households income each agent decide to invest to finance the energy community project. Agents communicate their electricity demand and the monetary contribution they are willing to commit to finance the joint investment, similar to Axtell (2002), and chose the level of individual contribution (x_i) that maximize their utility for collective consumption ($U_{i,2}$). The parameters D_{-i} and X_{-i} represent respectively the sum of electricity demand and the sum of contributions of all the agents involved in the bargaining process of coalition formation excluding agent i. Finally the parameter θ represents agents' preference for income and its complement $(1 - \theta)$ agents' preference for consumption.

The sum of the individual contribution should be enough to cover the investment proposed by the eco-innovator. Therefore, to reach an agreement, the agents involved in the bargaining process should satisfy the stability condition defined as follow:

$$I_{min} \leqq x_i + X_{-i} \leqq I_{max} \tag{4.5}$$

Differently form the model of Pasimeni and Ciarli (2018) that assumes that the installed capacity should cover the community demand (D), the present study does not impose such restriction. The excess in demand of the community is re-injected in the national grid, permitting to obtain extra income for the community.

The process of coalition formation unfold as follow. Each active node evaluates the joint investment proposed by the eco-innovator. First they check if it satisfy the stability condition 4.5; if it is satisfied the linked agents check their individual cost and utility in coalition; if the utility in coalition is higher compare to the utility of buying energy from a general provider $U_{i,2} \geq U_{i,1}$ and the cost is lower $c_{i,2} \leqq c_{i,1}$ they make a conditional decision that is stored as optimal. The decision is updated if a subsequent coalition offers lower costs compare to the optimal decision stored. If all agents are better off in the formed group, the different coalition of that size are further negotiated: all agents make explicit their optimal decision and the coalition that satisfy the Pareto efficiency is established. Pareto efficiency is reached when: i) all members maximize their utility in coalition, ii) no member has an incentive to move to another coalition, iii) no other agents would prefer to enter the coalition. Once the final decision in taken, if the coalition is formed, the agents involved break the existing links, and are not able to form new coalitions. As reported in Table 4.3, the coalition formation process determines the size of the energy community, the financed investment, therefore the PV capacity installed, and the PV production profiles.

It is important to note that the process of coalition formation does not assumed perfect rationality. Agents are boundedly rational in that they evaluate their utility not under all possible combination of coalitions, but only those actually available through the network formation process. Agents sense (i.e. acquire information) their neighbors individual contribution and energy demand, and evaluate their utility and cost in coalition accordingly.

Table 4.2: Model initialization

Variable	Parameter	Metrics	Value
Investment Size	S	kW	10 - 200
Investment Cost	I	€/kW	950 - 1250
Retail electricity price	p_1	€/kWh	0.023
PV electricity price	p_1	€/kWh	0.019
Consumption Profile	$d_i(t)$	kWh	Normal distribution
Income	e_i	€	Lognormal distribution ($\mu = 0, \sigma = 1$)
Preference for income	θ		0.5

Sub-model 3: REC Stability

The stability of the REC in the long term depends on the size of the community formed, its production profile, and the behavior of its member in terms of self-consumption profile. Self-consumed electricity allows the consumers not to pay fees that are usually collected with the

Table 4.3: Sub-model 2 outputs

Variable	Parameter	Metrics
REC Size	N	Number of participants
Installed PV capacity	$I(N)$	kW
Investment Cost	$I(N)$	€/kW
PV production profile	$g(t)$	kWh

network charges. Therefore, higher the level of self-consumption within the REC, higher the economic benefits for its members. However, since households may have very heterogeneous consumption profiles, that might not match the PV production profiles, the saving generated by the REC should be allocated in a way that satisfy each households. The stability of a community therefore depends on the way the values created by the community itself is shared (Abada et al., 2020; Tounquet et al., 2019).

Coalition Value

Based on the outputs from sub-model2 (see Table 4.3) , sub-model 3 estimates the value created by each coalition (REC) formed. It represents the characteristic function that gives the payoff (i.e. value) of a coalition of households that invest together in a PV panel.

Table 4.4: Sub-model 3 initialization

Variable	Parameter	Metrics
REC size	N	number
Consumption profile	$d_i(t)$	kWh
Installed PV capacity	$K(N)$	kW
PV investment Cost (function of capacity)	$I(N) = c$	€/kW
PV production profile	$g(t)$	kWh per kW
Variable grid tariff	α	€/kW
Fixed grid tariff	δ	€
Electricity retail price	$\beta(t)$	€/kWh
Electricity wholesale price	$\gamma(t)$	€/kWh

The model is initialized using the parameters reported in Table 4. considering a hourly granularity over a one year period, where a coalition of households of size N (formed in the sub-model2) invest in a PV system with capacity $K(N)$.For each REC the PV production at hour t is $K(N)g(t)$ and the excess in production is injected in the grid when $K(N)g(t) > \sum_{i\in N} d_i(t)$. The net demand of coalition N at hour t when the PV production does not cover the REC demand is $\sum_{i\in N} d_i(t) - K(N)g(t)$, while the net injection of coalition N at hour t when PV production exceeds the REC demand is $K(N)g(t) - \sum_{i\in N} d_i(t)$. Finally, the grid fees for a single consumers having a consumption profile $d_i(t)$ is $\alpha Max_t(d_i(t)) + \delta$.

$$
\begin{aligned}
v(N) = &\alpha[\sum_{i \in N} Max_t(d_i(t)) - Max_t(\sum_{i \in N} d_i(t))] \\
&+ \delta(n-1) \\
&+ \sum_{t=1}^{T} \beta(t)\Big(\sum_{i \in N} d_i(t) - \big(\sum_{i \in N} d_i(t) - K(N)g(t)\big)^+\Big) \\
&+ \sum_{t=1}^{T} \gamma(t)\big(K(N)g(t) - \sum_{i \in N} d_i(t)\big)^+ \\
&- cK(N)
\end{aligned}
\tag{4.6}
$$

The first term in 4.6 represents the aggregation benefit, i.e. reduction of the network fees. As stated in the REDII directive art 21, the Distribution System Operator (DSO) should treat a REC as it is one consumer, therefore reducing the peak demand of the REC compare to individual demand peaks. The second term represents the reduction of the fixed electricity fees, as only on meter is installed by the DSO (REDII art. 21). The third term represents the reduction of the electricity bills due to auto-consumption and the forth term the benefits from injection in the grid. Finally, the fifth term the PV installation costs. Therefore, the value of RECs materializes into reduced electricity bills (3rd term) and the payments received for the electricity injection in the grid (4th term). Based on the modeling assumption (i.e. retail tariffs are higher than the spot/wholesale price), in the absence of any compensation mechanism, it is more profitable to consume the electricity produced by the community than injected it into the grid. Therefore, a consumers will create more value higher the level of self-consumption (consumption during PV production).

In the process of creating value for the community, the heterogeneity in consumption behaviors raises the question of equity and stability. A consumer creating more value (consuming more during PV production) should receive an higher share of the value created by the community?

Allocation rules

In order to define how to allocate the value created by the REC members, it is first necessary to introduce the notion of stability (the core) of the community. A sharing rule of the value created by the REC members is stable if any households receives more then what it gets if he becomes an individual prosumers . Therefore, a stable allocation rule ensures that all REC members are satisfied with staying in the energy community.

Different allocation rules exists. The question is which one will ensure the stability of the REC. The empirical literature (Tounquet et al., 2019; Abada et al., 2020) show that simple allocation rules (per capita, per volume, per capacity) fail to ensure stability, while more elaborate sharing rules such as the marginal allocation rule and Shapley allocation rule meet the stability condition. Both allocation rules are based on the notion of marginal contribution. The marginal contribution of member i to coalition N is the additional value he brings to the other community members:

$$
MC(i, N) = v(N) - v(N - i) \tag{4.7}
$$

The marginal allocation rule gives a share of the whole value of the energy community to each member i proportionally to his marginal contribution, while the Shapley value gives to each member i a share of the whole value that is proportional to the average of all his marginal contributions to all possible coalitions. Both allocation are fair because they do not split according to the level of demand that can be decorrelated from the drivers of the value creation (self-consumption patterns), but split according to the real value brought by each member to the community. Moreover, both allocation rules ensure stability as they give more value to the ones who create it most (Tounquet et al., 2019; Abada et al., 2020).

However, the Shapley allocation rule is cumbersome computationally. Even if it has nice theoretical properties (additivity and separability), a theoretical comparison lies beyond the scope of the model, not affecting the stability of a REC. Therefore, in the model the marginal allocation rule is implemented (Tounquet et al., 2019). Starting from the parameters in Table 4.4, at the end of each year, once the data of consumption is known (allowing to accommodate any changes of consumption profiles of the households) the splitting of the value will give to each consumers i a benefit proportional to:

$$\begin{aligned}
&\alpha\Big[Max_t(d_i(t)) - Max_t\big(\sum_{i\in N} d_i(t)\big) + Max_t\big(\sum_{i\neq j} d_i(t)\big)\Big] + \delta \\
&+ \sum_{t=1}^{T} \beta(t)\big(d_i(t) - \big(d_i(t) - \frac{\sum_t d_i(t)}{\sum_{j,t} d_j(t)} Kg(t)\big)^{+}\big) \\
&+ \sum_{t=1}^{T} \gamma(t)\big(\frac{\sum_t d_i(t)}{\sum_{j,t} d_j(t)} Kg(t) - d_i(t)\big)^{+} \\
&- cK
\end{aligned} \tag{4.8}$$

Based on the marginal allocation rule the model finally turn to analyze how a stable allocation rule and the value created by the REC members is affected by financing mechanisms foreseen in the Italian regulatory framework.

Sub-model 4

The REDII directive states that citizens are entitled "to receive remuneration, including, where applicable, through support schemes, for the self-generated renewable electricity that they feed into the grid, which reflects the market value of that electricity and which may take into account its long-term value to the grid, the environment and society." (EC, 2018).

The Italian regulation regarding energy communities grants a premium tariff (110 €/MWh) for the shared electricity (GSE, 2020). It corresponds to the lowest value between the electricity fed into the grid and the electricity withdrawn from the points of connection on an hourly basis. The model therefore test the incentive mechanisms within the Italian regulatory schemes to evaluate its effect on the value created by the REC. In particular, it seeks to understand how much it affects RECs self-consumption patterns, and how it enable to create additional benefit for the energy community.

4.4 Conclusions

The proposed agent-based model aims to simulate the establishment of a REC in the form of an energy cooperative, which allows individuals to share the costs, risks and responsibilities of capital-intensive renewable energy projects in a democratic way, ensuring ownership and control of their energy assets (Caramizaru and Uihlein, 2020). Private consumers may decide to jointly invest and own a large-scale PV plant, to locally consume and share the produced electricity, which profitability is affected by the level of self-consumption within the community and by the compensation mechanisms envisage in a particular regulatory framework.

In simulating the establishment of RECs, the model considers the adoption decision as a collective action, taken by a group of consumers endogenously established in the model: consumers organise themselves following a bargaining process, as studied in game theory. In the operational phase, prosumers can save on energy charges and in the final electricity bill if they replace costlier electricity withdraw from the grid with self-consumption of locally generated renewable electricity (Agency, 2018). The analysis leaves aside the aspect of complete autarky and storage, assuming grid connection and focus on the analysis of compensation mechanisms influencing the financial viability of energy communities, as the remuneration of the surplus of PV production influence the level of self-consumption within the community and therefore the value the community creates.

The representation of key dynamic mechanisms in the system evolution, along with explicit representation of policy interventions allows the use of the model for ex-ante policy evaluation. This is implemented by changing the parameters of the model and observing the relative outcomes, which can aid the design of policy interventions in different ways (Hammond, 2015). It permits to understand intended and unintended consequences of the interventions, to detect unnoticed opportunities by identifying leverage points induced by small shifts generated by the policy intervention (i.e. tipping points), and to elucidate on its play out in the long term. The model is not built to make point predictions, but serves to explore what might happen under a range of possible potential scenarios (Gilbert et al., 2018).

The heterogeneity of the socio-economic and cultural conditions in each Member States entails different barriers for the engagement of citizens (Massey et al., 2018). To account for this variability, the model will be calibrated using Italian data. Specific households socio-economic characteristics, PV costs and production profiles, and energy market design shape the viability of REC. However, when available, different empirical variables might be used to calibrate the model (Van Daalen et al., 2002) shading light on the specific enabling framework most suitable in other contexts.

The study focuses on the individual role in enabling social innovations looking at the social and economic motives in joining a community project. It does not account for the complexities involved in the cooperative set-up (e.g. site searching with technical and feasibility assessment, project development including grid connection and procurement). It also ignores the distributional concerns arising from a high-penetration of self-consumption, which might lead to unfair distribution of network charges, taxes, and levies to the other consumers (Dehler et al., 2017). Self-consumption rise the profit of PV systems and lower the stress on the electricity distribution grid. However, as the share of distributed energy resources increase, to compensate for the loss in network charges, retailer might increase the costs for the remaining consumers, inducing to create negative externalities to the rest of the community.

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APPENDICES

A. Stochastic Dominance Hypothesis

Proposition 1: *Highly concerned households adopt more environmentally sustainable technologies than little (or no) concerned households.*

Proposition 2: *Strong financial concerns translate to greater adoption of energy saving technologies.*

Proposition 3: *Households with positive attitude towards environmental matters adopt more than households with little (or no) concerns toward environmental problems.*

Corollary 1: *Low financial concerns lead households to not adopt energy saving technologies.*

Corollary 2: *Negative attitude toward environmental problems leads households to not adopt energy saving technologies.*

Proposition 4: *Strong financial and environmental concerns jointly lead to higher adoption of energy saving technologies.*

Corollary 3: *Households that are jointly strongly concerned about the environmental and financial matters adopt more than households that expressed little (or no) concerns.*

Corollary 4: *Negative attitude toward environment and low financial concerns lead households to avoid adopting energy saving technologies.*

Proposition 5: *Financial concerns lead to greater adoption than environmental concerns.*

Corollary 5: *Households with low (or no) financial concerns adopt more than households with little (or no) environmental concerns.*

B. Correlation Analysis

The Chi-Squared test of independence is used to analyze 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 Figure 3.2)

C. Sensitivity Analysis β

The image below reports the sensitivity analysis of the parameter β that weights economic, behavioural and social factors in the agent's adoption rule.

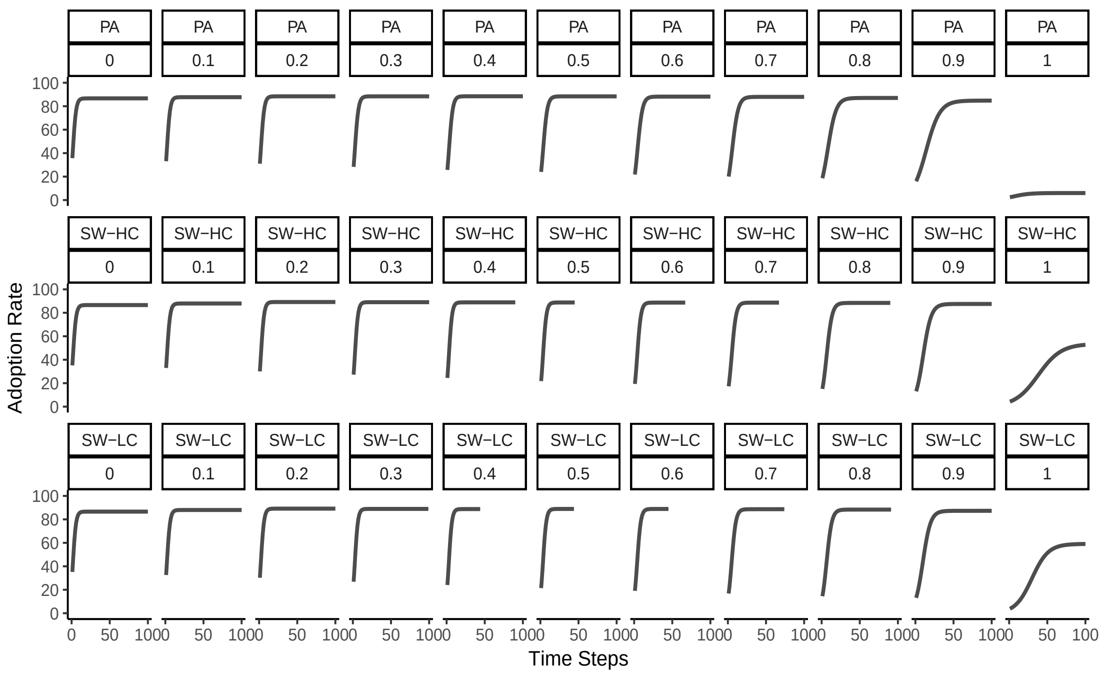

Figure C.1: Sensitivity analysis of β per type of network. Type of networks: PA preferential-attachment; SM-HC small-world high-cluster; SM-LC small-world low-cluster. Source: Authors' calculation.

D. Results Policy Simulation

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

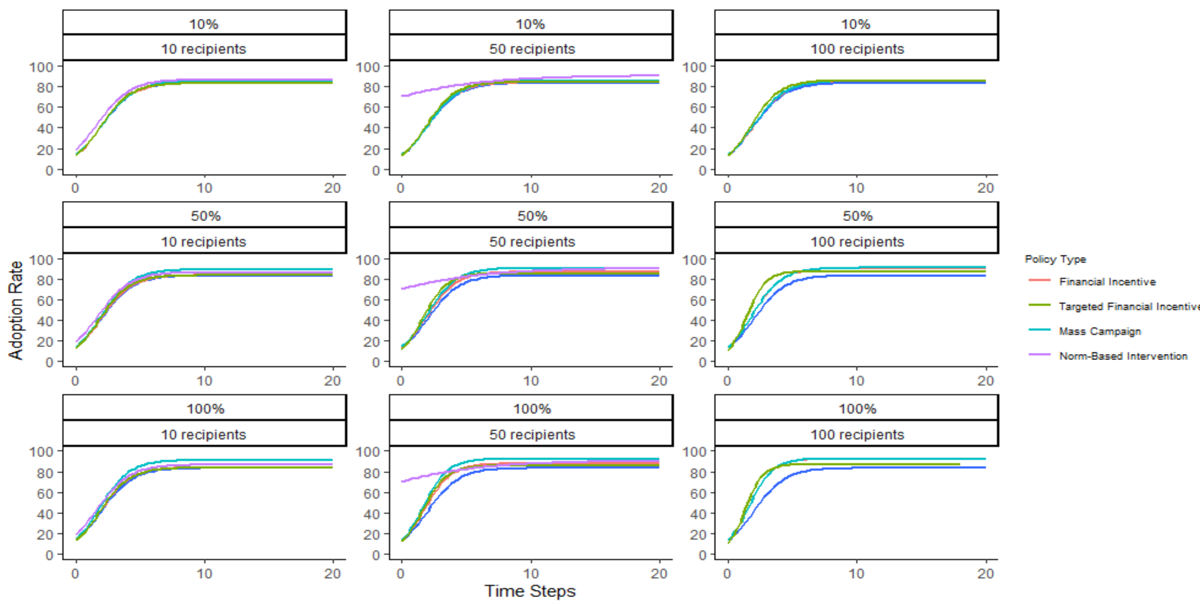

Figure D.1: Policy simulation results for $\beta = 0$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

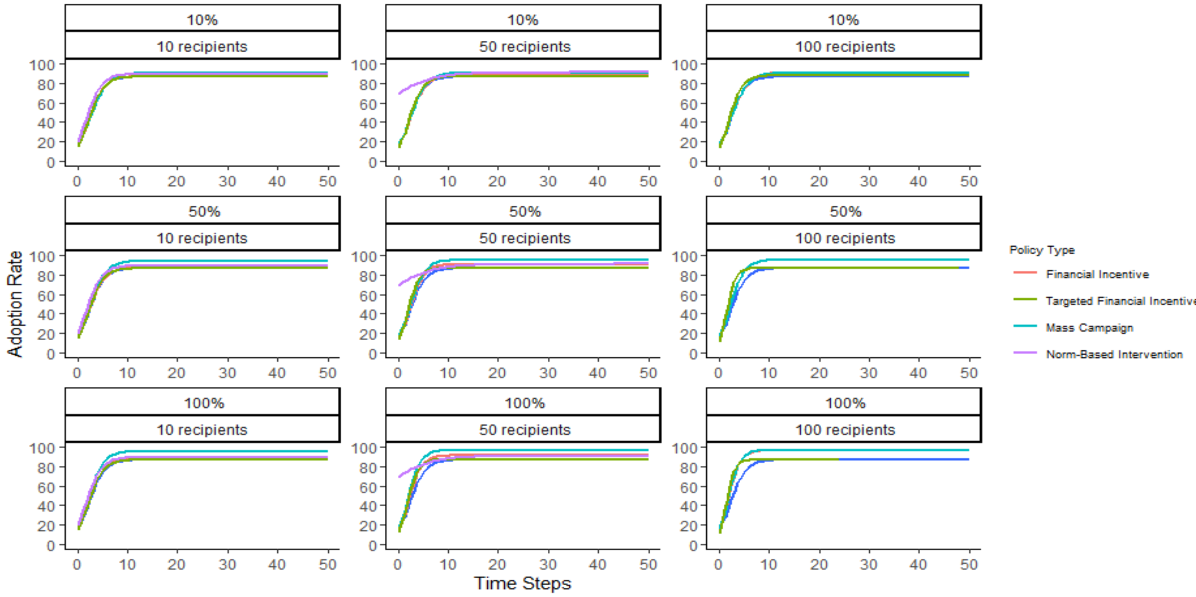

Figure D.2: Policy simulation results for $\beta = 0.1$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

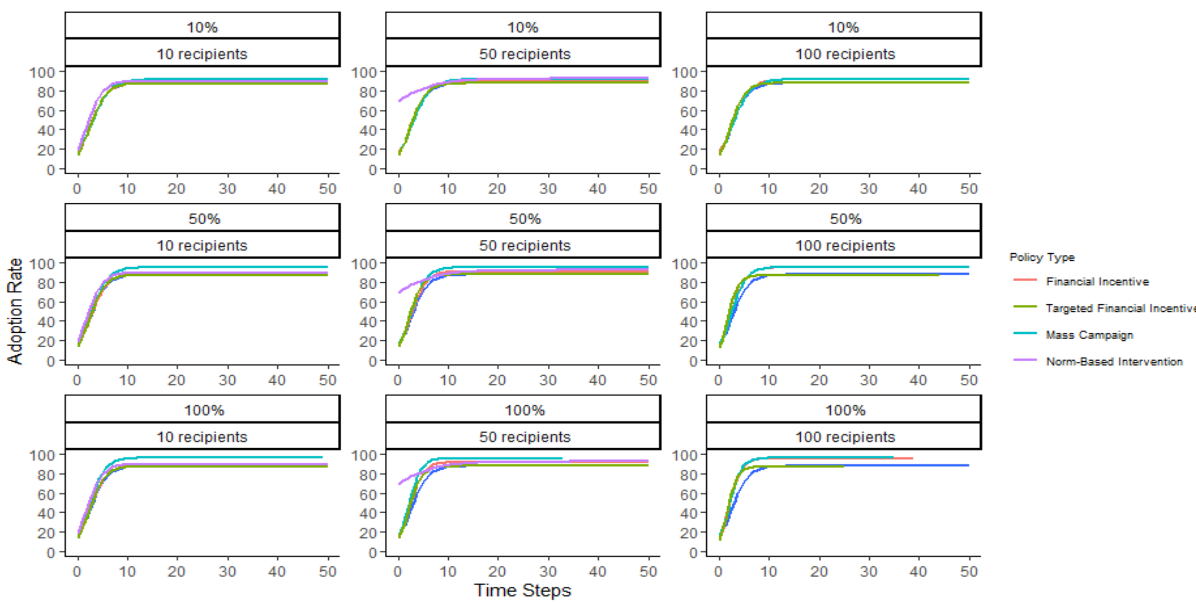

Figure D.3: Policy simulation results for $\beta = 0.2$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

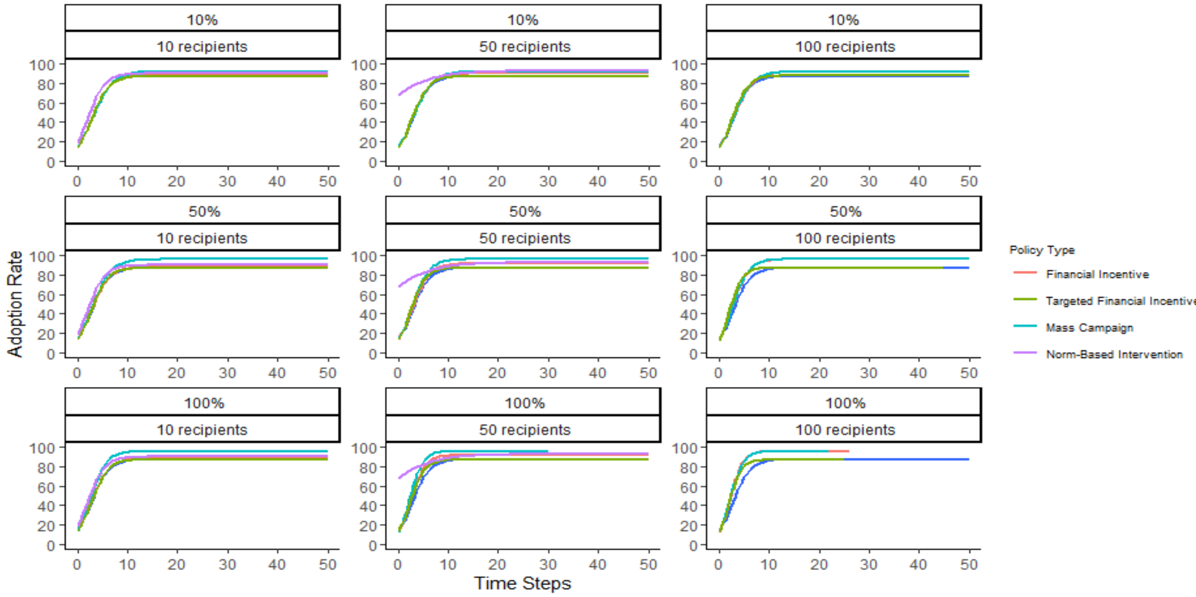

Figure D.4: Policy simulation results for $\beta = 0.3$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

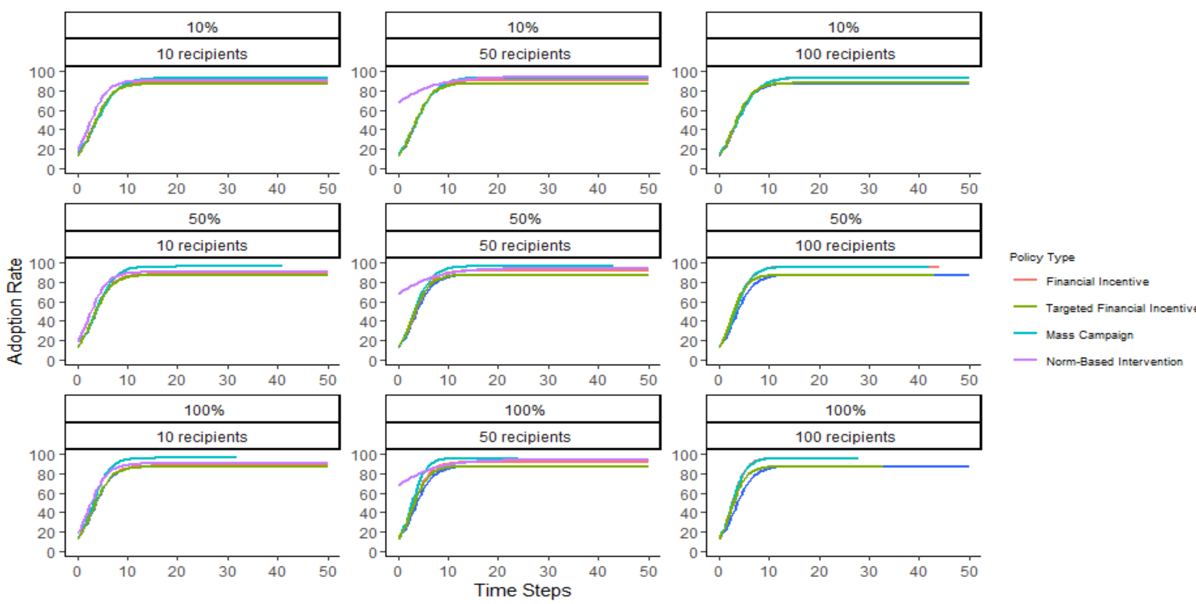

Figure D.5: Policy simulation results for $\beta = 0.4$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

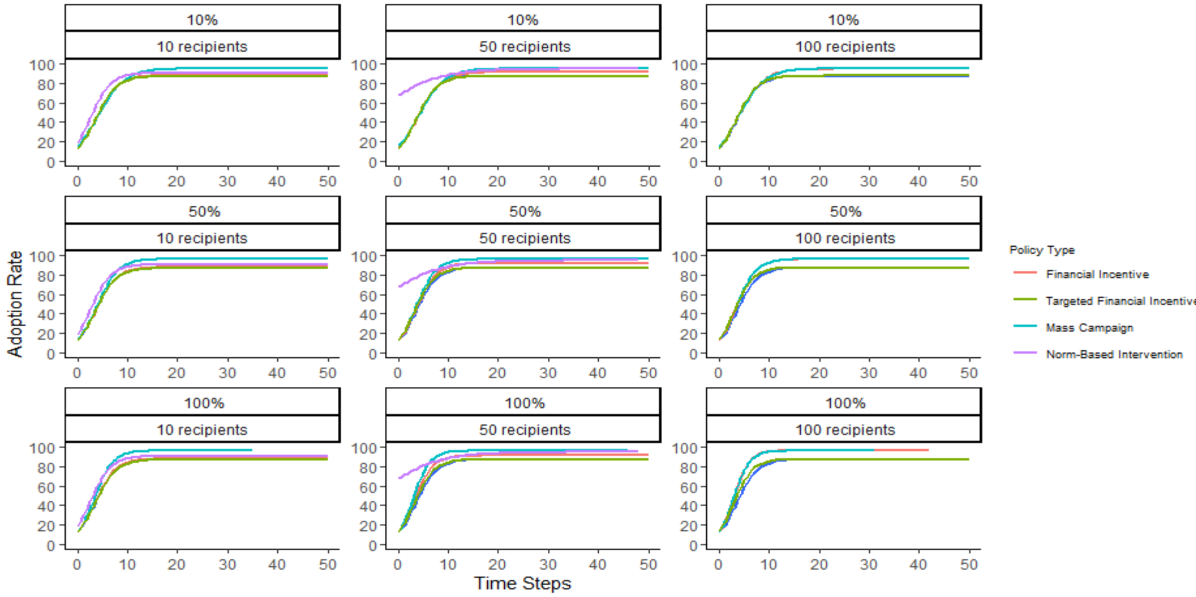

Figure D.6: Policy simulation results for $\beta = 0.5$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

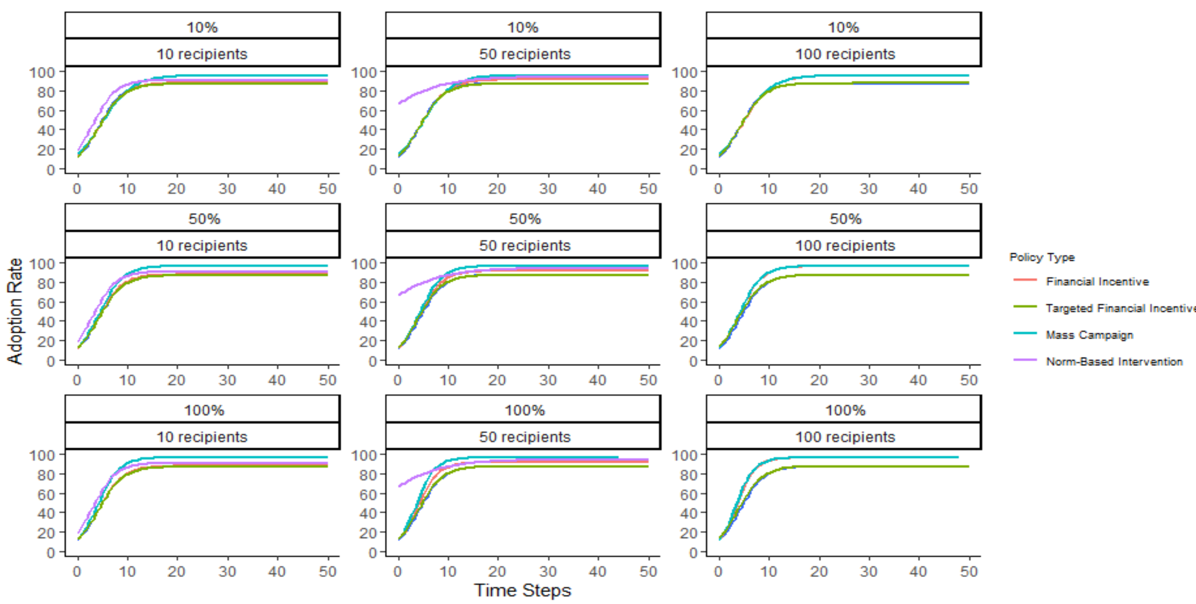

Figure D.7: Policy simulation results for $\beta = 0.6$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

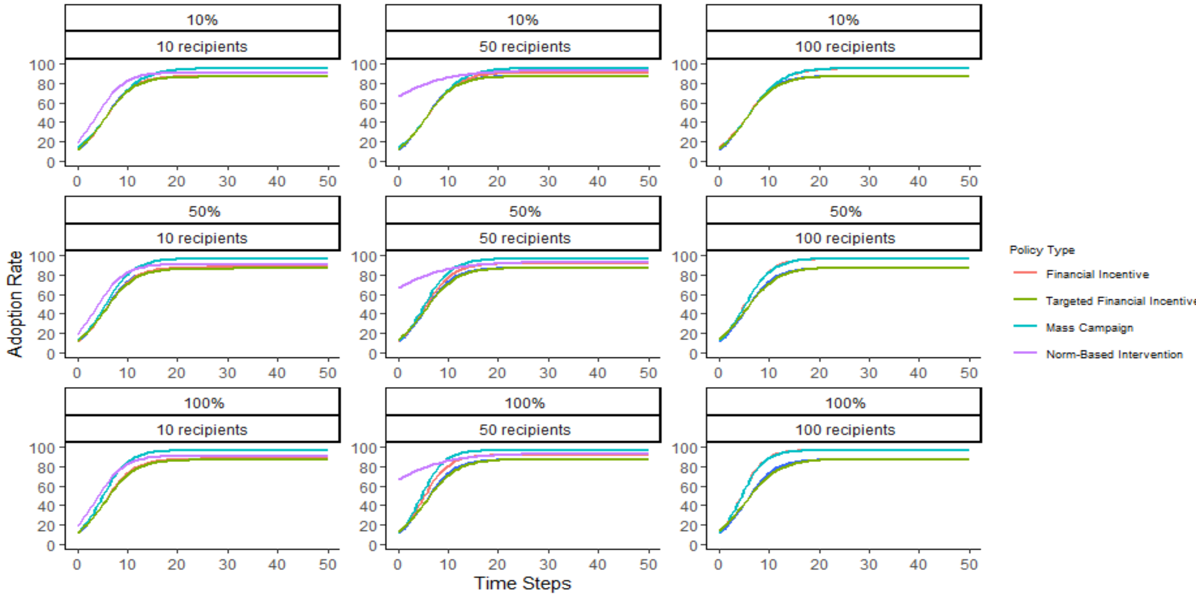

Figure D.8: Policy simulation results for $\beta = 0.7$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

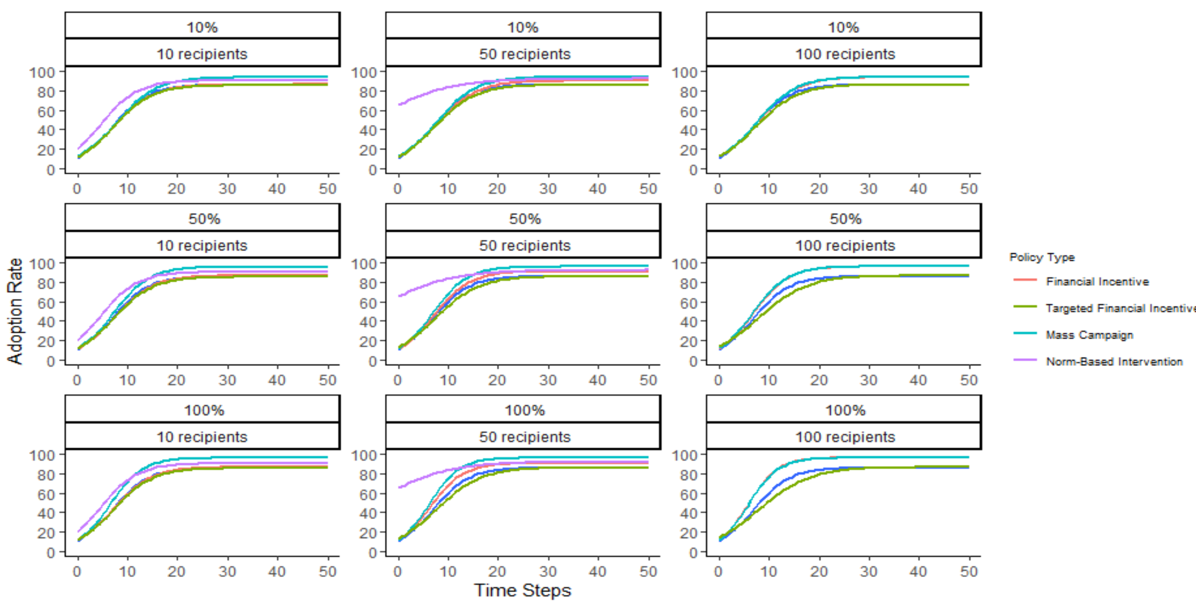

Figure D.9: Policy simulation results for $\beta = 0.8$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

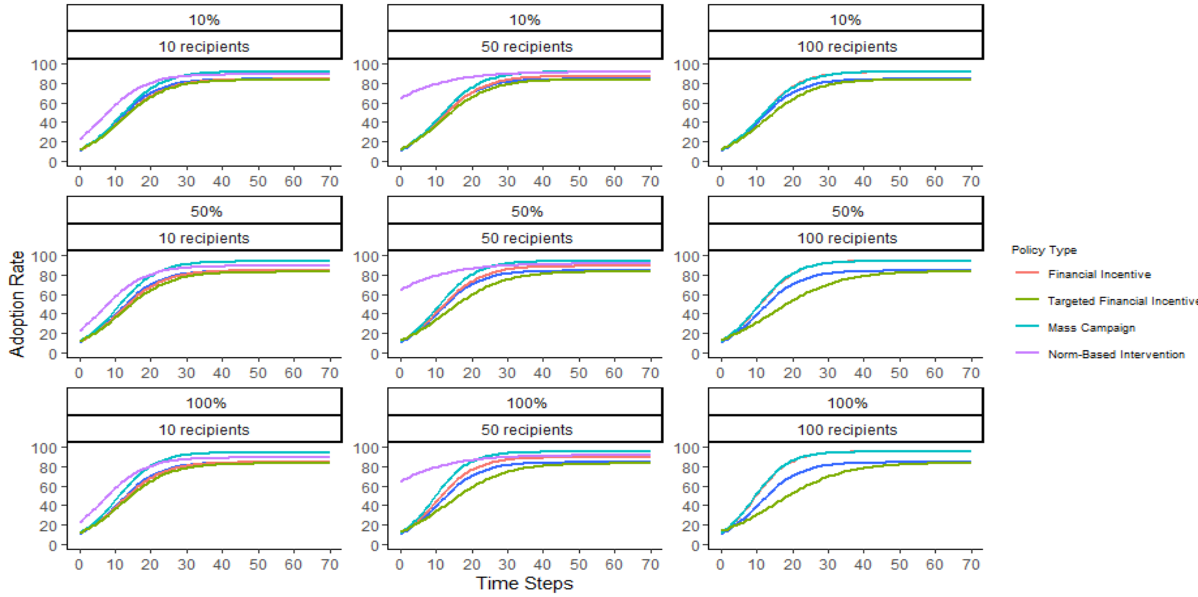

Figure D.10: Policy simulation results for $\beta = 0.9$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

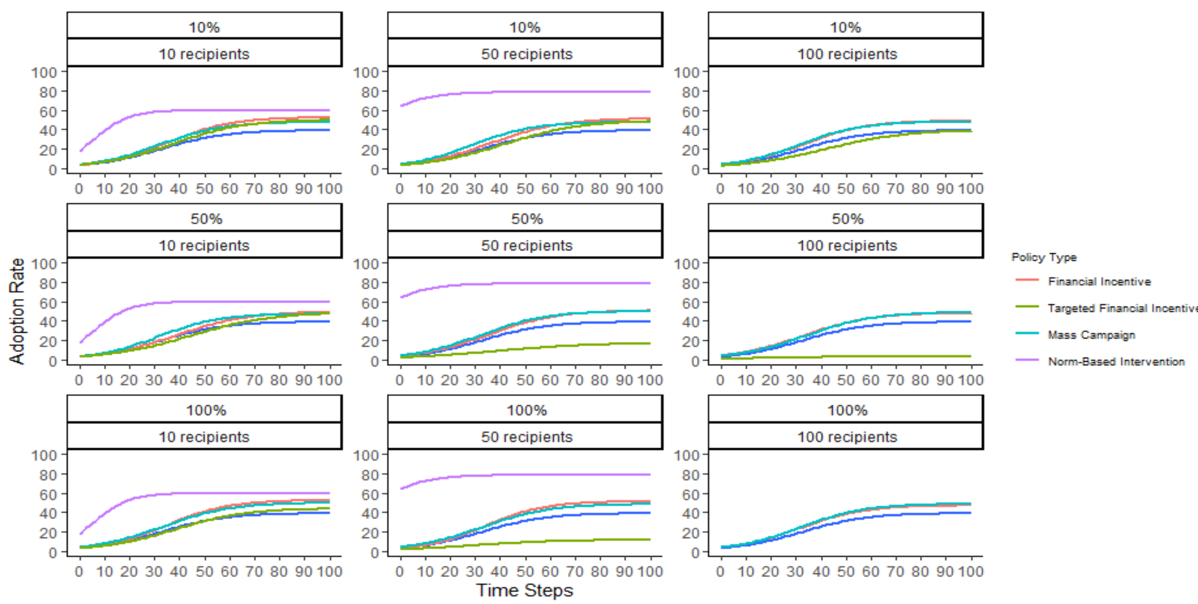

Figure D.11: Policy simulation results for $\beta = 1$. The blue line represents the simulation results for the baseline model. The x axis represents the discrete simulated time, the length of one time step is not specified. The y axis represents the average adoption rate observed after 100 simulations runs. Source: Authors' calculation.

E. NetLogo Implementation

```
turtles-own [
 adoptability?
 adopted?
 innovators?

 environmental-concern
 income
 degree
 normal_bc

 relative-cost
 relative-cost-normalized

 imitation
 neighbors-influence
 adoption-rule
]

;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;;                            ;;;;
;;;;  Initial setup procedures  ;;;;
;;;;                            ;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

to setup1
  clear-all
  create-network
end


to setup2
```

```
    file-open "subsetHO.100.txt"
    while [not file-at-end?]
        [
            let next-node file-read
            let node-income file-read
            let node-ec file-read

            ask turtle next-node
            [set income node-income set environmental-concern node-ec ]
]
  file-close
end


to setup3
  ask turtles [
    set relative-cost  (1) / income
    set degree count link-neighbors
  ]
      let mx max [relative-cost] of turtles
      let mn min [relative-cost] of turtles
      let den (mx - mn)

  ask turtles [
    set relative-cost-normalized (( relative-cost - mn ) / den)
    set imitation (1 - environmental-concern)

    if income = 0.1
        [set color blue
         set adoptability? false]
  ]

  ask turtles [
    let bc nw:betweenness-centrality
    let max_bc max [nw:betweenness-centrality] of turtles
    let min_bc min [nw:betweenness-centrality] of turtles
    let den_bc (max_bc - min_bc)
    set normal_bc (bc - min_bc) / (max_bc - min_bc)
  ]
  seed
  reset-ticks
end

;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
```

```
;;;;                              ;;;;
;;;; create the social network ;;;;
;;;;                              ;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

to create-network
    if network-type = "small-world-high-cluster"
        [ create-small-world-high-cluster]
    if network-type = "small-world-low-cluster"
        [ create-small-world-low-cluster]
    if network-type = "preferential-attachment"
        [ create-preferential-attachment ]
end



;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;                          ;;
;; small-world-high-cluster ;;
;;    (Kleinberg Model)     ;;
;;                          ;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;


to create-small-world-high-cluster
  nw:generate-small-world turtles links 10 10 3.9 false [
    set size 2
    set shape "person"
    set adoptability? true
    set adopted? false
    set innovators? false
    set color green
  ]
end






;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;                         ;;
;; small-world-low-cluster ;;
```

```
;;    (Kleinberg Model)    ;;
;;                         ;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;


to create-small-world-low-cluster
  nw:generate-small-world turtles links 10 10  0.1 false   [
    set size 2
    set shape "person"
    set adoptability? true
    set adopted? false
    set innovators? false
    set color green
  ]
end



;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;                             ;;
;;   preferential-attachment   ;;
;; (Barabasi-Albert algorithm) ;;
;;                             ;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;


to create-preferential-attachment
  nw:generate-preferential-attachment turtles links 100 1 [
    set size 2
    set shape "person"
    set adoptability? true
    set adopted? false
    set innovators? false
    set color green
  ]
end




;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
```

```
;;;;
;;;;
;;;;  seed the population with first adopter seed options:
;;;;
;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;


to seed
  if seeding-method = "random" [
    ask n-of innovators turtles with [ color = green]
    [
      set adoptability? true
      set adopted? true
      set innovators? true
      recolor
    ]
  ]

  if seeding-method = "betweenness" [
    ask max-n-of innovators turtles with [ color = green ]
    [ nw:betweenness-centrality ]
    [
      set adoptability? true
      set adopted? true
      set innovators? true
      recolor
    ]
  ]

    if seeding-method = "eigenvector" [
    ask max-n-of innovators turtles with [ color = green]
    [ nw:eigenvector-centrality ] [
      set adoptability? true
      set adopted? true
      set innovators? true
      recolor
    ]
  ]

 if seeding-method = "marginal" [
   ask min-n-of innovators turtles with [ color = green ]
   [nw:closeness-centrality] [
      set adoptability? true
```

```
      set adopted? true
      set innovators? true
      recolor
    ]
  ]
end



;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;
;;;;          ;;;;
;;;; report ;;;;
;;;;          ;;;;
;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;


to-report global-clustering-coefficient
  let closed-triplets sum
  [ nw:clustering-coefficient * count my-links *
  (count my-links - 1) ] of turtles
  let triplets sum [ count my-links * (count my-links - 1) ] of turtles
  report closed-triplets / triplets
end




;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;
;;;;          ;;;;
;;;; Policy ;;;;
;;;;          ;;;;
;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;


to implement-policy ; botton Policy in the Interface
 if policy-type  = "policy_1ec" [ policy_1ec ]
 if policy-type  = "policy_2ec" [ policy_2ec ]
 if policy-type  = "policy_1c" [ policy_1c ]
 if policy-type  = "policy_2c" [ policy_2c ]
end
```

```
;; MASS CAMPAIN - Behavioural intervention
to policy_1ec
  ask n-of population turtles [
    set environmental-concern environmental-concern + awareness
    set color white ]

  ask turtles [
  if environmental-concern > 1
    [set environmental-concern 1]
     set imitation (1 - environmental-concern)]
end


;; TARGETED NORM BASED INTERVENTION - Imitation intervention
to policy_2ec
  foreach sort-on [normal_bc] turtles
  [
    ask max-n-of population turtles [normal_bc]
    [
      set adopted? true
      set color white
    ]
  ]
    ask turtles [
    if environmental-concern > 1
    [set environmental-concern 1]
    set imitation (1 - environmental-concern)]
end


;; FINANCIAL INCENTIVES - Economic intervention NOT TARGETED
to policy_1c
  ask n-of population turtles [
    set  relative-cost-normalized relative-cost-normalized -

    relative-cost-normalized * rebate
    if relative-cost-normalized < 1 [set adoptability? true]
    set color white ]
end


;; FINANCIAL INCENTIVES - Economic intervention TARGETED
to policy_2c
   ask min-n-of population turtles [income]
```

```
    [
      set  relative-cost-normalized relative-cost-normalized -
      relative-cost-normalized * rebate
      if relative-cost-normalized < 1 [set adoptability? true]
      set color white  ]
end


;;;;;;;;;;;;
;;;;;;;;;;;;
;;;;    ;;;;
;;;; go ;;;;
;;;;    ;;;;
;;;;;;;;;;;;
;;;;;;;;;;;;


to go
  ask turtles with [ not adopted? ]  [ decide-to-adopt  adopt]
  ask turtles [ recolor ]
  tick
  if all? turtles [ adopted? = true or adoptability? =
  false or adoption-rule <= 0] [ stop ]
end



;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;;                    ;;;;
;;;; adoption decision ;;;;
;;;;                    ;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;


to decide-to-adopt
   if any? link-neighbors [
    let neighbors-adopters link-neighbors with [ adopted? = true ]
    let social-environment count link-neighbors
         if social-environment = 0 [stop]

     set neighbors-influence (
     (  count neighbors-adopters * imitation ) / social-environment)
  ]
```

```
end



to adopt
   if any? link-neighbors [
    set adoption-rule (((1 - b) / 2) *
    ( environmental-concern - relative-cost-normalized ) + b *
    neighbors-influence)
    if (adoptability? = true and random-float 1.0 <
    adoption-rule) [set adopted? true]
  ]
end


to recolor
  if adopted? [ set color red ]
end

to layout
  layout-spring turtles links 1 14 1.5
  display
end

to-report ec-adopters
  let ec [environmental-concern ] of turtles with [adopted? = true]
  report ec
end

to-report c-adopters
  let c [income ] of turtles with [adopted? = true]
  report c
end

to-report node-degree
  let n-degree [degree ] of turtles
  report n-degree
end

to-report normalized-bc
  let n-bc [ normal_bc] of turtles
  report n-bc
end
```