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Linking of a multi-country discrete choice experiment and an agent-based model to simulate the diffusion of smart thermostats

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ABSTRACT

In this paper, we link findings from a demographically representative discrete choice experiment (DCE) in eight European countries on the adoption of smart thermostats with an agent-based model (ABM) in a methodologically consistent way. We employ the ABM to simulate the diffusion pattern of smart thermostats until 2030 and to examine the effects of subsidies and recommendations by specific agents. Our findings highlight the importance of allowing for within- and across country heterogeneity in preferences for these policies and for technology attributes such as heating cost savings. Further, social interactions reinforce country differences in technology stock in the starting year of the simulations. We find that subsidies moderately accelerate the diffusion of smart thermostats, but they are less effective in countries with a large stock of smart thermostats in the starting year, strong preferences for heating cost savings, and when smart thermostats lead to a strong reduction in heating costs. For some countries, targeting subsidies at particular socio-economic groups (in our case low-income households) slightly mitigates free-riding effects. Our policy simulations further imply that recommendations by energy providers or by energy experts accelerate the diffusion of smart thermostats compared to recommendations by peers.

1. Introduction

The residential sector accounts for about 40 percent of total energy use and CO_2 emissions globally, highlighting the need to study the diffusion of energy-saving technologies in this sector. In recent years, agent-based models (ABMs) have often been used to study the diffusion of sustainable energy technologies among households (Li et al., 2015; Li et al., 2017). For instance, previous studies have analysed the effects of policies to spur the diffusion of renewable and cogeneration technologies for electricity generation (Bruckner et al., 2005; Chappin and Dijkema, 2009; Palmer et al., 2015), of renewable-based heating systems (Sopha et al., 2013; McCoy and Lyons, 2014; Jensen et al., 2015; Rai and Robinson, 2015; Robinson and Rai, 2015; Snape et al., 2015), of energy-efficient household appliances (Schwarz and Ernst, 2009, Chappin and Afman, 2013; Hicks and Theis, 2014; Hicks et al., 2015; Zhang et al., 2016, Moglia et al., 2018; Chappin et al., 2019;), of insulation measures (Friege et al., 2016), and of electric vehicles (EVs) (Köhler et al., 2009; Zhang et al., 2011; Noori and Tatari, 2016; Shafiei et al., 2012; Plötz et al., 2013; Wolf et al., 2016; Sun et al., 2019).

ABMs are particularly well suited to model the diffusion of new technologies because their flexible architecture allows modellers to explicitly incorporate social interactions and to account for agent heterogeneity and for different environments. Thus, ABMs may integrate findings from behavioural research which suggests that technology adoption by individuals or households depends on social interactions (Rai and Henry, 2016) such as peer adoption and word-of-mouth recommendations by peers or experts (e.g. Kiesling et al., 2012). In addition, ABMs may explicitly account for agent heterogeneity by allowing for heterogeneity in decision processes or reservation prices (e.g. Cantono and Silverberg, 2009; Kiesling et al., 2012) as well as heterogeneity by socio-demographic characteristics (e.g. Zhang et al., 2011; Hicks and Theis, 2014; Hicks et al., 2015). Because ABMs allow for path dependency, lock-in effects, and the passing of time (e.g. Hafner et al., 2020), they also capture differences in the levels of development across markets. ABMs may therefore be employed to design and assess policies promoting the adoption of sustainable technologies and behaviours,

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thereby accounting for social interactions, heterogeneity across agents, and the scale of adoption over time across different geographic areas. In this sense, ABMs enable a systematic analysis of the emergent dynamics induced by such policies.

To parameterize ABMs, modellers rely on theory (e.g. Jager, 2017), ad-hoc assumptions (e.g. Hesselink and Chappin, 2019) and empirical results. For example, findings from empirical studies on agent utility for specific technologies (or technology characteristics) may be used to parameterize the agents' decision model in an ABM (e.g. Holm et al., 2016).

Only few studies analysing household adoption of sustainable energy technologies with ABMs, however, employ individual-level survey data. For instance, to simulate the adoption of lighting systems, Hicks and Theis (2014) and Hicks et al. (2015) distinguish various groups of households based on socio-economic characteristics. Inspired by survey data, these groups receive different utility weights for particular technology attributes, but the link between the weights and the survey data remains ad-hoc. On the basis of psychological factors of the Theory of Planned Behavior (TPB) (Ajzen, 1985), Jensen et al. (2015) develop specific heuristics for different consumer groups; these heuristics are empirically calibrated based on a study by Schwarz and Ernst (2009) on water-saving shower heads. Studying the adoption of solar photovoltaics by households, Rai and Robinson (2015) use linear regression models based on survey data to operationalize psychological factors. Using location data from the survey, they populate the social network (on the basis of clustering socio-demographical characteristics), which in turn influences the evolution of attitudinal factors. Sopha et al. (2013) simulate the diffusion of wood-pellet heating systems in Norway, assuming household utility to be governed by the TPB and by peer adoption. They derive the weights of the various components of the utility function from an empirical survey. Shafiei et al. (2012) and Noori and Tatari (2016) study the adoption of electric vehicles in Iceland and the United States, respectively, distinguishing various household groups. In both studies, utility weights associated with particular automobile characteristics are derived in an ad-hoc manner from a survey of the Danish population. Thus, existing studies employing individual-level survey data typically rely on ad-hoc assumptions to obtain utility weights.

A few studies use a more systematic approach to derive utility weights from survey data as input for an ABM. Analysing the adoption of electric vehicles in Ireland, McCoy and Lyons (2014) distinguish between income and environmental utility. They calculate environmental utility based on information from a representative survey on participants' environmental attitudes and their stated energy efficiency behaviour. To calculate income utility, McCoy and Lyons (2014) use information on social class, tenure and age. To aggregate the individual components, they employ an ad-hoc ranking scheme which is assumed to vary by socio-economic groups. Wolf et al. (2016) study electric vehicle adoption in Berlin (Germany) and represent survey respondents as individual agents. Their modelling focuses on the role of emotions which are represented through an artificial neural network obtained from survey data and an experimental study. Studying the diffusion of photovoltaic systems in Italy, Palmer et al. (2015) introduce an agent's utility function including payback time, environmental benefits, income, and links to other adopters in the same category (constructed using Sinus-Milieu data for Italy). They calibrate the utility weights using data on the historic diffusion of photovoltaic systems in Italy. Finally, Zhang et al. (2011) simulate individual decisions to adopt electric vehicles in Germany using findings from a discrete choice experiment (DCE) to specify the parameters in the utility function. However, because their DCE is conducted with automobile experts, their findings may not be representative for the population at large.

In this study, we employ an ABM to simulate the diffusion of smart thermostats in eight European countries until 2030; we directly integrate findings from demographically representative surveys using DCEs in these countries. We analyse the DCEs via mixed logit models and establish a hard link between the utility weights obtained through the DCEs for various technology attributes and those used in the ABM. We also use the DCE results to account for preference heterogeneity. Further, we simulate the effects of subsidies and of recommendations by energy providers and experts compared to recommendations received from peers. Subsidies and recommendations are particularly relevant to spur the diffusion of new technologies. Because smart thermostats involve high perceived levels of complexity and technological and financial risks (Rijsdijk and Hultink, 2009; Ehrenhard et al., 2014; Wilson et al., 2017), subsidies and expert recommendations may be needed to overcome these additional barriers. We simulate the effects when all households are eligible to receive a subsidy and compare findings with a scenario where only low-income households are eligible to receive a subsidy.

This paper contributes to the literature in multiple ways. First, relying on large-sample representative surveys, the parameters governing technology choice in our ABM are empirically grounded. In particular, building on Zhang et al. (2011), the parameter estimates obtained from the DCEs are used to specify the parameters of agents' utility functions in the ABM. Thus, our methodology involves a hard link between a demographically representative DCE and individual-level survey data with an ABM. Lack of empirically grounded behaviour inputs has often been considered a main weakness of ABMs (e.g. Crooks, 2008; Durlauf, 2012; Chattoe-Brown, 2013; Scheller et al., 2019).

Second, we incorporate preference heterogeneity in a methodologically consistent way in an ABM reflecting household heterogeneity in responses to social interactions and to policy, and in key attributes of smart thermostats. To model this general preference heterogeneity, we use the standard deviations of the estimated means of the parameters as calculated by the mixed logit models. In the ABM, this heterogeneity is conceptualized as a source of uncertainty. Because the scant literature combining DCEs and ABMs did not employ mixed logit models, this approach is innovative. In addition, we allow for preference heterogeneity which is specific to particular socio-demographic characteristics such as age and income. This also allows for a more fine-grained understanding of the role of socio-demographic characteristics and their interactions with policy for the diffusion of smart thermostats. In this sense, our approach addresses challenges frequently directed at ABMs pertaining to limited empirical foundation and restrictive behavioural assumptions (e.g. Crooks, 2008; Durlauf, 2012; Chattoe Brown, 2013; Scheller et al., 2019).

Third, our empirical analysis includes eight European countries. To our knowledge this is the first study integrating information from multi-country representative household surveys into an ABM. Thus, our approach explicitly recognizes heterogeneity in individual preferences across countries. It also allows the analysis of the role of differences in starting conditions (here the stock of smart thermostats in the starting year of the simulations) when analysing the effects of social interactions and policies on the diffusion of technologies over time. Because we include eight countries throughout the analysis, we show the implications of the differences in preferences and starting conditions between countries.

Fourth, existing studies employing ABMs to analyse the diffusion of energy-efficient technologies have focused on appliances (Hicks and Theis, 2014; Hicks et al., 2015; Chappin et al., 2019), and insulation measures (Friege et al., 2016). Typically, these analyses involve either replacement (appliances, windows, heating systems) or improvement (insulation measures) of existing technology infrastructures that are already widely diffused. In contrast, ABMs have not been employed to analyse the diffusion of smart energy devices such as smart meters, smart appliances and smart thermostats. This study focuses on smart thermostats. Smart thermostats provide direct feedback on thermal energy consumption. By tracking thermal energy consumption patterns, sensing changes in human behaviour and environmental stimuli, and relying on artificial intelligence, some smart thermostats also offer users automatized heating control (e.g. Chan et al., 2008). In addition, smart

Table 1
Levels of different attributes considered in the thermostat choice experiment.

Attribute	Levels	Variable name
Heating bill	1% less, 5% less, 10% less	*savings*
Remote temperature control	Yes, No	*remote*
Display of changes in energy consumption	Yes, No	*display*
Recommendation	by friends or colleagues (baseline)	*recom_expert*
	by independent energy experts	*recom_provider*
	by your energy provider	
Purchase price	€150, €180, €210, €240, €270, €300	*price*
Subsidy	€0, €20, €40, €60	*subsidy*

thermostats often allow users to monitor and adjust the temperature remotely through a smartphone application. Thus, smart thermostats generally enable households to more efficiently heat their homes (e.g. avoiding keeping temperatures unnecessarily high at night or when the dwelling is not occupied) and save up to 10% of heating costs without loss of comfort (Liang et al., 2012; Kleiminger et al., 2014). Because space heating offers a large potential to meet ambitious energy and climate policy targets such as the 55% reduction goal for greenhouse gas emissions in the European Union (European Commission, 2021), studying the diffusion of smart thermostats seems particularly worthwhile. Further, because smart thermostats are in the early stages of diffusion, accounting for household heterogeneity and for differences across countries is particularly relevant when analysing and modelling their diffusion.

We organize the remainder of the paper as follows. Section 2 describes the methods in detail (both for the discrete choice experiment and the agent-based model). Section 3 presents and discusses the results. Section 4 summarizes the main findings and critically reflects on the limitations of our study.

2. Methods

In this section, we present the design of the DCE and describe the core elements of the ABM model.

2.1. Description of DCE

DCEs are conceptually based on the Lancasterian theory of demand (Lancaster, 1966) and the random utility framework (McFadden, 1974). They simulate a hypothetical market environment by asking participants to successively choose among multiple technology alternatives which differ in terms of their combination of attribute levels. Assuming that participants choose the technology that yields the highest utility in a given choice set, econometric methods are used to estimate the weights associated with the technology attributes in the utility function.

2.1.1. Survey

A multi-country online survey was fielded in July and August 2018 in France, Germany, Italy, Poland, Romania, Spain, Sweden, and the United Kingdom (UK) using quota sampling. For each country, the samples were representative in terms of age, gender, income and regional dispersion. Survey participants belonged to an existing online household panel provided by the survey institute Norstat. Only individuals involved in their household's decisions for purchases, expenditures and bills such as utility bills or household appliance shopping were eligible to participate in the survey. In each country, respondents participated in DCEs and were randomly assigned to DCEs on different technologies or policies, including one DCE on smart thermostats. In addition, in the general part of the survey, respondents were asked to provide information on standard socio-economic variables, on energy expenditures, and on characteristics of their dwelling.

2.1.2. DCE for thermostats

In the[1] choice experiment, respondents made a series of choices between smart thermostat purchase alternatives ("We would like to know which heating control device you would prefer, if you were making a purchase and these were your only options"). Table 1 shows the attributes and levels selected for the DCE. In particular, recommendation reflects the social interaction component of the utility function which is characteristic of ABM models, and may be influenced by policy. Subsidy captures government policy to accelerate the diffusion of smart thermostats. We document the exact wording of the framing in Fig. A.1 in Appendix A.

Using Ngene (ChoiceMetrics, 2014), we employed a Bayesian efficient design (Sándor and Wedel, 2001), where priors were obtained from a pilot study with 50 participants from a separate online access panel in the UK. The decisions consisted of 12 scenarios divided into two blocks. Participants were randomly assigned to one of the blocks and therefore every respondent successively answered six scenarios with two choice alternatives. Instead of directly offering an opt-out option as a third-choice alternative, we designed a dual response approach: after participants had chosen their preferred alternative, they were asked in a follow-up question to indicate on a scale from 1 ("very unlikely") to 4 ("very likely") how likely they were to actually buy their preferred alternative if it was available on the market. If a participant answered "unlikely" or "very unlikely", the response was excluded from the econometric analyses. Fig. A.2 in Appendix A shows a scenario as seen by respondents from the UK.

We use a mixed logit model (MXL) to analyze the DCE. In contrast to a standard conditional logit model, an MXL allows for unobserved individual-specific heterogeneity of the parameters β_n across individuals (Revelt and Train, 1998) and hence does not rely on the Independence of Irrelevant Alternatives (IIA) assumption. Therefore, in addition to mean estimates for the parameters, MXL estimation also produces standard deviations for the parameter estimates.

Equation (1) reflects the (latent) utility function of participant n choosing alternative j in choice set t

$$U_{njt} = \beta_n X_{njt} + \varepsilon_{njt}, n = 1, ..., N, j = 1, 2, t = 1, ..., T \quad (1)$$

where N stands for the number of participants, T for the number of choice sets, and J for the number of alternatives. In our case, N differs by country, T=12 and J=2. X_{njt} is a vector of smart thermostat attributes,

[1] Tu et al. (2021) provide a more detailed description of the DCE and the econometric approach, a review of the literature on smart thermostat adoption, and a justification of the attributes and levels based on previous literature. In this paper, we employ the same data as Tu et al. (2021) as input for the ABM; our econometric analysis includes a different set of socio-economic variables to better reflect the focus of this paper.

ε_{njt} refers to an error term assumed to follow an extreme-value Gumbel distribution, and β_n is a vector of random parameters which varies among participants. This vector is characterized by density function $f(\beta|\theta)$ with a vector of parameters θ (Train, 2003). We assume all parameters to follow a normal distribution.

In our case, the utility function is:

$$\begin{aligned} U_{njt} &= (\beta_{n,1} + \beta_2 elder + \beta_3 lowinc) \times price \\ &+ (\beta_{n,4} + \beta_5 elder + \beta_6 lowinc) \times subsidy \\ &+ (\beta_{n,7} + \beta_8 heat + \beta_9 elder + \beta_{10} lowinc) \times savings \\ &+ (\beta_{n,11} + \beta_{12} elder + \beta_{13} lowinc) \times recom\_provider \\ &(\beta_{n,14} + \beta_{15} elder + \beta_{16} lowinc) \times recom\_expert \\ &+ (\beta_{n,17} + \beta_{18} elder + \beta_{19} lowinc) \times remote \\ &+ (\beta_{n,20} + \beta_{21} elder + \beta_{22} lowinc) \times display + \varepsilon_{njt} \end{aligned} \quad (2)$$

The variable *price* denotes net price (in euros)[2], i.e. the price minus any subsidies as in Train and Atherton (1995). Heating cost savings (in percentage of heating costs) are denoted as *savings. Rec_provider* and *rec_expert* are dummy variables taking on the value 1 if the thermostat is recommended by an energy provider or by an independent expert, respectively. Recommendation by friends or colleagues is used as the baseline level and therefore not included in equation (2) to avoid singularity of the regressor matrix[3]. The two last attributes reflect features typical for smart thermostats. First, *remote* is a dummy variable that takes on the value 1 if the thermostat can be controlled through a remote device such as a smart phone. Second, *display* is a dummy variable that takes on the value 1 if the thermostat displays changes in energy consumption when the temperature is modified. To account for household differences in heating costs, following the choice experiment, respondents were asked to indicate their actual heating costs. In case respondents did not know their heating costs or provided unreasonable values, we estimated heating costs based on building type, building age, living area, geographical region, heating system, and isolation measures.[4] Reported or estimated heating costs were then divided by 100 and an interaction term between the scaled heating costs (*heat*) and *savings* was included in the model. If respondents with higher heating costs value an additional 1% decrease in their heating costs more than households with lower heating costs, this interaction term is positive. In addition, our model allows for differences in individual preferences which are due to individual characteristics. Therefore, equation (2) includes interaction terms of the attributes with two dummy variables, *lowinc* and *elder* to consider the effects of income and age on preferences for attributes. Empirical studies have found income and age to be related with household adoption of heating-related investments in retrofit measures or low-carbon heating systems (e.g. Michelsen and Madlener, 2012, 2016; Schleich, 2019, Schleich et al., 2019; Spyridaki et al., 2020). The findings on the interaction terms also provide guidance for policy. In particular, policies targeted at particular socio-economic groups such as low-income households may result in more efficient use of resource because the free-rider problem is smaller. That is, a large share of households may have adopted a smart thermostat even without a subsidy. Finally, modelers can easily obtain information on income and age of the population from official statistics unlike for attitudes, for example. More specifically, *lowinc* took on the value 1 if household income (based on the survey questionnaire) belonged to the lowest income category in a country. Second, *elder* took on the value 1 if the respondent was at least 55 years old (based on the survey questionnaire).[5] All coefficients associated with the interaction terms enter the estimation via MXL as fixed parameters. We estimate the model via simulated log likelihood methods, using 500 Halton draws (Train, 2003).

2.2. Description of ABM

2.2.1. Introduction to EMLab-Consumer

The simulations are performed with EMLab-Consumer, an ABM that simulates household investments in appliances and heating systems. We provide a detailed description of the model in Appendix D, which follows the ODD+D (overview, design concepts and details including human decision making) protocol - an established standard for describing ABMs that include human decision-making (Müller et al., 2013). The full model code is open source.[6] A preliminary version of EMLab-Consumer is presented in Chappin et al. (2019). The model contains different types of agents (households and suppliers) as well as appliances. Households can own a variety of appliances, including a smart thermostat. Over a period of decades, households make use of their appliances and invest in replacement. They also interact with other households through a social network, sharing information on past adoption of appliances.

The agents in the simulation are generated on the basis of the survey data (see section 2.2.2 for details) and are distributed in a virtual 2-dimensional space. Their social network is generated through a semi-randomized process: we generate a scale-free network between agents on the basis of ad-hoc assumptions. In the simulation, we populate agents with three links on average, where links are formed within a relatively small radius around the agents' virtual locations.

When households decide to replace an appliance, they decide on which appliance to purchase and where to buy it. The decision logic uses the utility function as specified in equation (2) for the DCE (see the details provided in section 2.1 and 2.2.2). Beyond the components in the utility function, households are assumed to be limited in their decision in the number of options they consider, and affected by what is recommended by friends through their social network. Households are further assumed to consider the properties of the current appliance they are replacing.

The model is implemented in NetLogo.[7] The model itself is data-free and all parameters (household data, technology data, utility function data, and default policy parameters) are read from csv files at the start of the simulation. The set-up of the model allows for expansion in terms of policies, technology types, etc.

2.2.2. Integrating findings from the discrete choice experiments and the general part of the survey

The agents in the simulation are generated from the households in the survey in the sense that each survey participant corresponds to one agent. Although the survey participants are individuals, we assume that their decisions are representative of the household decisions. This assumption seems justified by the eligibility criteria that were used for survey participation. The decision logic is presented in Fig. 2. We integrate information from the general part of the survey pertaining to

[2] Note that the survey was always conducted in the country's currency and we used the same monetary amounts across countries. To account for purchase power parity and round up the monetary values shown to the DCE participants, we used the following exchange rates for the non-Euro countries: Poland 1€ = 3 PLN; Romania 1€ = 3 RON, Sweden 1€ = 10 SEK, and UK 1€ = £1.

[3] In all simulations below, households receive a recommendation from an energy provider or an independent expert, but not from both.

[4] Self-reported heating costs were assumed to be unreasonable when the difference between estimated and self-reported annual heating costs was larger than 750 euros. Our findings are virtually the same when we use 650 and 850 euros instead of 750 euros as the cut-off value.

[5] Due to panel restrictions, we only recruited participants between 18 and 65 years of age. As reported in Table 3, the share of respondents above 55 years of age lies between 14% (Romania), and 26% in the UK. We refrained from using a higher cut-off value to define elderly respondents as this would have led to very small subsamples of elder participants in some countries.

[6] See http://emlab.tudelft.nl.

[7] NetLogo is a popular open source agent-based modelling platform. See http://ccl.northwestern.edu/netlogo for more information.

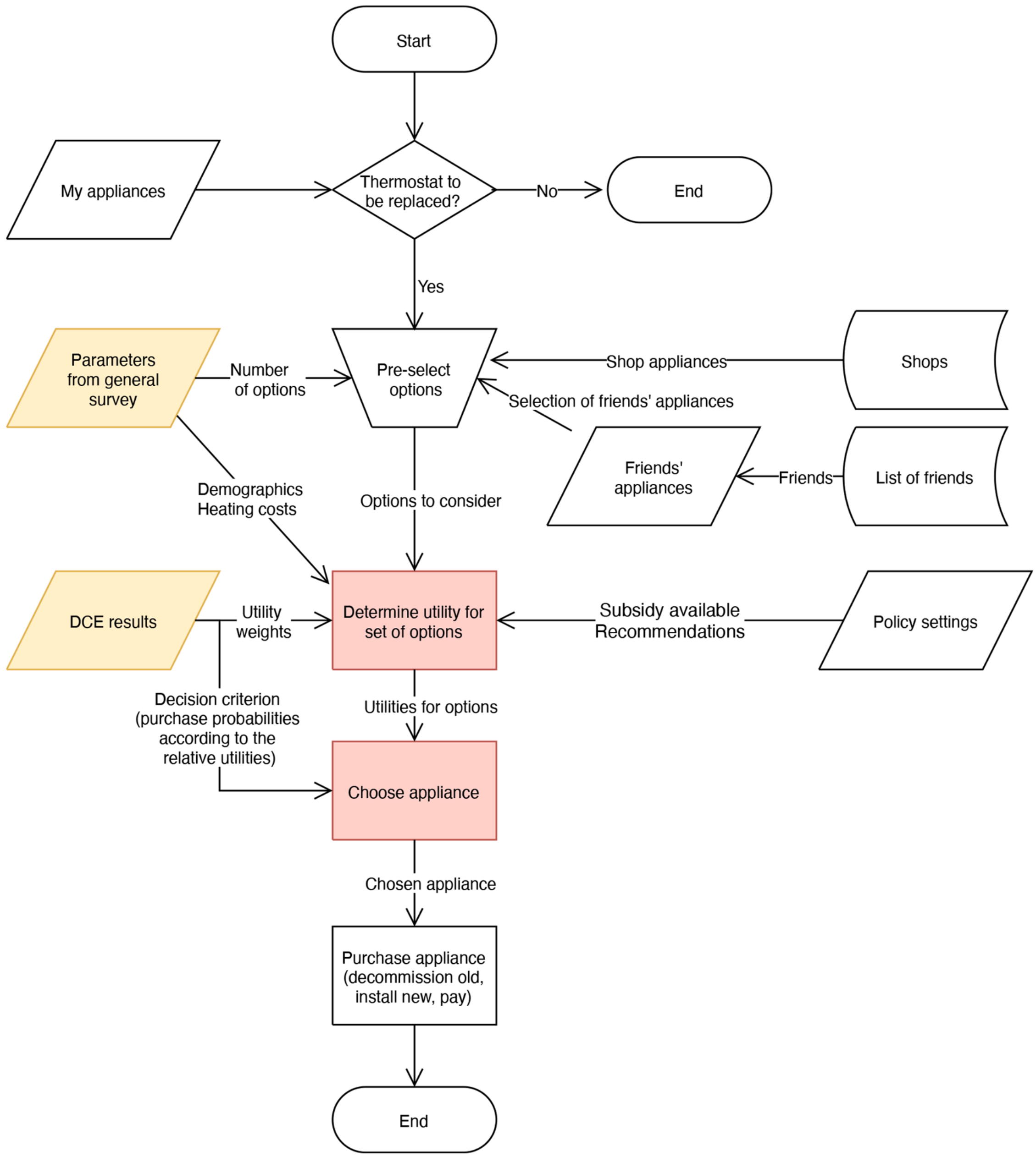

Fig. 1. Decision logic for a household agent, as implemented in the ABM.

participant age and income, how many options participants typically consider when replacing an appliance, and whether they already own a smart thermostat.

The results of the DCEs as described in section 3.1 are directly fed into the ABM (hard link). More precisely, the estimated parameter means from the MXL are used as choice model parameters in the ABM. Accordingly, the thermostat purchase decision is driven by (i) technology attributes, i.e. the net *price* of the thermostat, *remote control* and energy saving display features, (ii) whether it is *recommended* by friends or colleagues, an independent expert, or by the energy provider, and (iii) differences in the parameter estimates by sociodemographic characteristics of the decision maker, i.e. age and disposable income. Age and income are used to determine groups distinguishing elderly and low-income households from others.

The variables mentioned above are affected by policies. A subsidy will lower the retail price for agents. When only a particular demographic subset of the population is eligible for a subsidy, the model accounts for the fact that the subsidy is only available for agents from that group. Further, in contrast to the baseline recommendation from friends (which is implemented through the social network), when other recommendation policies are used (for instance through experts or energy providers), the extra utility brought through these recommendations is obtained from the DCE results.

Further, information from the survey on the number of options that participants typically consider when deciding on a new appliance is applied as a filter on the gross set of appliances that is evaluated by the agents in the decision logic. Agents observe the appliances of a limited number of other households in their social network (which forms the baseline recommendation, for which no policy needs to be represented) and add these appliances to the set of appliances they consider in their purchase decision.

In addition to these properties, data regarding yearly heating costs (obtained through the survey) are included, because they affect the actual heating cost savings that are to be expected from adopting a smart thermostat. To capture heating costs in the ABM, we include information on gas price profiles available from Eurostat for each country. Except for

Table 2
Results of mixed logit model for DCE on thermostat purchase decisions.

	France	Germany	Italy	Poland	Romania	Spain	Sweden	UK
Mean								
price	-0.0058***	-0.0051***	-0.0067***	-0.0074***	-0.0053***	-0.0073***	-0.0077***	-0.0073***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
subsidy	0.0003	-0.0088***	-0.0011	0.0009	0.0033**	-0.0057***	0.0013	-0.0063***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
savings	0.2301***	0.3636***	0.1986***	0.3536***	0.2282***	0.2344***	0.2297***	0.1947***
	(0.026)	(0.033)	(0.020)	(0.034)	(0.025)	(0.017)	(0.035)	(0.018)
recom_provider	0.4681***	0.4762***	0.4498***	-0.0304	0.7565***	0.3090***	0.1269	0.2289***
	(0.103)	(0.111)	(0.103)	(0.098)	(0.097)	(0.078)	(0.110)	(0.080)
recom_expert	0.2820**	0.7397***	0.5014***	0.2553*	0.8739***	0.3849***	0.3995***	0.1525*
	(0.116)	(0.127)	(0.106)	(0.134)	(0.127)	(0.084)	(0.124)	(0.090)
remote	0.3517***	0.3626***	0.4924***	0.9168***	0.6762***	0.6142***	0.8472***	0.4168***
	(0.092)	(0.105)	(0.083)	(0.118)	(0.093)	(0.065)	(0.129)	(0.070)
display	0.3240***	0.4176***	0.4015***	0.5572***	0.5849***	0.4227***	0.6563***	0.3848***
	(0.084)	(0.090)	(0.077)	(0.089)	(0.083)	(0.059)	(0.111)	(0.065)
heat_x_savings							0.0073***	
							(0.002)	
elder_x_price								
elder_x_subsidy								
elder_x_savings	0.1399***			-0.1081**				
	(0.042)			(0.043)				
elder_x_recom_provider			0.4253*			0.4346**		
			(0.235)			(0.197)		
elder_x_recom_expert	0.3492		0.4547*	0.6734***		0.4594**		0.2490
	(0.230)		(0.250)	(0.237)		(0.213)		(0.157)
elder_x_remote				-0.6169***				
				(0.207)				
elder_x_display								
lowinc_x_price		-0.0046**						
		(0.002)						
lowinc_x_subsidy							-0.0079*	
							(0.004)	
lowinc_x_savings				-0.0969***	-0.0504*			
				(0.036)	(0.026)			
lowinc_x_recom_provider								
lowinc_x_recom_expert				-0.2432	-0.3658**			
				(0.203)	(0.165)			
lowinc_x_remote								
lowinc_x_display								
Standard deviation								
price	0.0056***	0.0074***	0.0056***	0.0048**	0.0070***	0.0043***	0.0041	0.0060***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
subsidy	0.0043	0.0137***	0.0114***	0.0128***	0.0106***	0.0155***	0.0168***	0.0109***
	(0.008)	(0.004)	(0.003)	(0.004)	(0.004)	(0.002)	(0.004)	(0.003)
savings	0.1914***	0.2638***	0.1451***	0.2434***	0.1747***	0.1818***	0.2339***	0.1528***
	(0.025)	(0.032)	(0.021)	(0.026)	(0.021)	(0.016)	(0.030)	(0.018)
recom_provider	0.0546	0.0271	0.0101	0.0408	0.2815	0.0081	0.1693	0.0144
	(0.332)	(0.354)	(0.315)	(0.287)	(0.320)	(0.161)	(0.413)	(0.151)
recom_expert	0.5527***	0.5099*	0.2143	0.6165***	0.6169***	0.4732***	0.3422	0.2461
	(0.197)	(0.276)	(0.369)	(0.219)	(0.178)	(0.160)	(0.360)	(0.314)
remote	-0.0062	0.5656***	0.2234	0.8145***	0.5119***	0.0601	0.9750***	0.0970
	(0.237)	(0.177)	(0.260)	(0.146)	(0.146)	(0.265)	(0.168)	(0.425)
display	0.0053	0.0229	0.0008	0.0950	0.4414**	0.0163	0.6242***	0.0055
	(0.200)	(0.440)	(0.153)	(0.219)	(0.177)	(0.171)	(0.186)	(0.145)
Number of participants	500	573	429	474	468	763	575	632
Number of observations	3042	3760	3454	4050	4588	6430	3654	4420

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Poland and Sweden, natural gas accounts for the highest fuel share in residential heating in the countries in our sample.[8]

As illustrated in red in Fig. 1, the utility function is the core element of the decision logic of the agents and governs household appliance choice. The ABM logic essentially conceptualizes this as a replacement question, but agents may start out with a regular thermostat or no thermostat at all (which are modelled identically in the ABM). After the expiration of each thermostat's lifetime (set to 10 years in the model), whether there is no thermostat at all, a regular thermostat or a smart thermostat, household decision-makers first select the shops at which they would like to buy their appliances. Based on the stock of

[8] Considering only one fuel type is a simplifying assumption and may not adequately reflect the actual conditions, especially not in Poland and Sweden.

thermostats in these shops[9], they select the options for which they then determine and compare the level of their utility. Purchase probabilities are calculated from:

$$P_{ni}(\beta_n) = \frac{\exp(\beta_n X_{nit})}{\sum_{j=1}^{J} \exp(\beta_n X_{njt})}, n = 1, ..., N, j = 1, 2 \tag{3}$$

where N stands for the number of participants, and J for the number of alternatives. $\beta_n X_{nit}$ is the expected utility for alternative i for agent n. The coefficients β_n are directly taken from the DCE (as indicated in yellow in Fig. 1). One time step in the simulation represents one year where all households have followed this decision logic.

In each simulation run, the coefficients of individual agents are varied according to the standard deviations of the estimated parameter means obtained from the MXL (see Table 2).[10] This allows us to analyse the emergent differences in adoption patterns that are due to general preference heterogeneity.

2.2.3. Technology Data

The smart thermostats in the simulations vary by attributes such as price and features. We collected information on attributes from 39 smart thermostats available on the market at the time of collection and these were consistently applied to all eight countries. These thermostats provide a range of attribute levels which covers the variety of products offered in the countries included in this study. At the same time, it may cover more options than consumers would typically see in local stores.[11] Table B.1 in Appendix B lists the smart thermostats used in the model. To balance the simulations, we added 39 regular thermostats.[12] Regular thermostats are assumed to have no effect on energy consumption and to be available without additional cost to the household. This set-up forms the fall-back option, which is interpreted as households not switching to a smart thermostat, or simply choosing the default option that comes with the heating system or home and is assumed to be included in the price for the heating system or home. We may therefore use the same decision logic to simulate whether a smart thermostat is purchased and the type of smart thermostat chosen.

2.2.4. Design of policy scenarios

For each country included in the survey, we conduct separate simulations for two types of policies which may promote the diffusion of smart thermostats: subsidies and recommendations. Both types of policies were included in the DCE. We distinguish several policy scenarios.

First, in the *subsidy scenario,* we consider a subsidy of either 30 or 60 euros per smart thermostat. For most thermostats in our analysis, this means a considerable reduction in net price.[13] We further distinguish whether all households are eligible to receive a subsidy or whether only low-income households are eligible to receive a subsidy. Second, in the *recommendation scenario,* we study the effects of recommendations provided by energy experts or energy providers compared to recommendations provided by friends in the agents' social network. Thus, we run two recommendation scenarios, one for recommendations by energy experts (*expert recommendation scenario)* and one for recommendations by energy providers (*provider recommendation scenario)*. Specifically, for both recommendation scenarios, we assume half the smart thermostats to be recommended by energy experts or energy providers.

The levels chosen for the subsidies and the shares of energy experts and energy providers recommending a particular smart thermostat are in the range of those used in the DCE. While it may be difficult to realize the upper levels of the subsidies (i.e 60€) and a share of 50% of thermostats receiving a recommendation in practice, the simulation results indicate the effects such ambitious policies may have on the diffusion of smart thermostats, and hence provide valuable insights for policy-making.

We conduct 100 runs per policy setting to capture the differences between individual model runs. The main sources of differences are the following. First, parameter uncertainty, which is captured by the standard deviations of the estimated means of the parameters β_n in equation (2) affects the utility weights and therefore utilities for the options and, consequently, purchase choices. Second, the actual sets of options that are considered by the agents differ between each decision round: the number of options considered are selected at random from the larger set of possible options (pre-selected relevant options in Fig. 1). Third, actual choices are random and depend on the relative utility of the considered options (see equation 4). Fourth, differences between the generated social networks affect the run because of the options that are considered by friends.

3. Results

We first present the results of the DCE and then the findings of the policy simulations with the ABM.

3.1. Results of the DCE

When estimating the parameters in equation (2), most of the interaction terms were found to be insignificant. We then re-estimated the models using only the interaction terms that had been significant at $p<0.1$ in the first estimation. Further, to limit the potential effects of hypothetical bias, we only used scenarios in which respondents indicated that they were "somewhat likely" or "very likely" to purchase their preferred option. This criterion resulted in two to twelve observations per respondent. The exact number of respondents in the DCE on thermostat purchase decisions in each country is shown in the last row of Table 2, which reports the results of the final models.

Looking first at the bottom part of Table 2, we note that over half the standard deviations are statistically significant which corroborates our use of a MXL model.[14] This also implies heterogeneity of parameter estimates across individuals, which we model as a key source of uncertainty in the simulations with the ABM.[15] Furthermore, it means that allowing preferences for attributes to vary by age and income only partially captures heterogeneity across individuals' valuation of the attributes.

We now briefly turn to the results for the estimated means of the parameters which are shown in the upper part of Table 2. These values are used to specify the utility function in the ABM. The coefficients associated with the main effects (i.e. *price, subsidy, savings, recom_provider, recom_expert, remote, and display*) capture the preferences of those participants where all interaction terms are set to zero, i.e. participants younger than 55 living in households with higher income levels than the

[9] See next section for details.

[10] We report these in the lower part of Table 2. For the simulation runs, we only varied the standard deviations if they were statistically significant at $p<0.1$.

[11] In contrast, developing country-specific option sets for appliances, would allow for local policy analyses.

[12] If the number of smart thermostats was higher than the number of regular thermostats, households would be more likely to choose a smart thermostat due to the higher probability of having more smart thermostats in the consideration set than regular thermostats.

[13] For cheap smart thermostats, these subsidy levels may imply negative net price. Based on additional simulations where we cap the net price at zero, we find that the results presented in section 3 are not sensitive to negative net prices.

[14] In addition, we conducted likelihood ratio tests on the joint significance of standard deviations. The null hypothesis that standard deviations of the preference parameters are jointly equal to zero can be rejected in all countries (p-values < 0.001).

[15] In the ABM simulations, we set standard deviations to 0 if the p-value was above 0.1.

Table 3
Variable means and standard deviations (in parentheses) used in the simulations.

Variables	France	Germany	Italy	Poland	Romania	Spain	Sweden	UK
Households	1765	1232	1045	2048	1184	1317	2035	1855
Age (years)	42	43	43	42	39	42	42	43
	(13)	(13)	(12)	(13)	(12)	(12)	(14)	(13)
Elderly (%)	22	23	18	22	14	18	25	26
Low income (%)[17]	27	34	41	23	42	41	24	45
Smart thermostats in 2018 (%)	11.9	5.4	13.6	6.3	31.2	17.8	3.4	13
Heating costs (€/year)	1366	745	581	684	336	541	894	841
	(1301)	(1090)	(794)	(960)	(458)	(606)	(1083)	(982)
Number of options considered	6.5	6.3	9.9	11.3	12.0	6.3	11.0	9.9&
	(6.2)	(5.5)	(6.9)	(7.0)	(8.3)	(5.4)	(7.0)	(7.0)

[17] Note that the category low income was based on the quotas used by the market research company in each country, which explains the different percentages across countries. The following cut-off values for monthly after-tax income were used in each country to determine the low income category: up to 1999€ in France, Italy, and Spain, 1499€ in Germany, 8860 PLN (2953€) in Poland, 1800 RON (600€) in Romania, 199999 kr (1999€) in Sweden, and £1579 (€1579) in the UK.

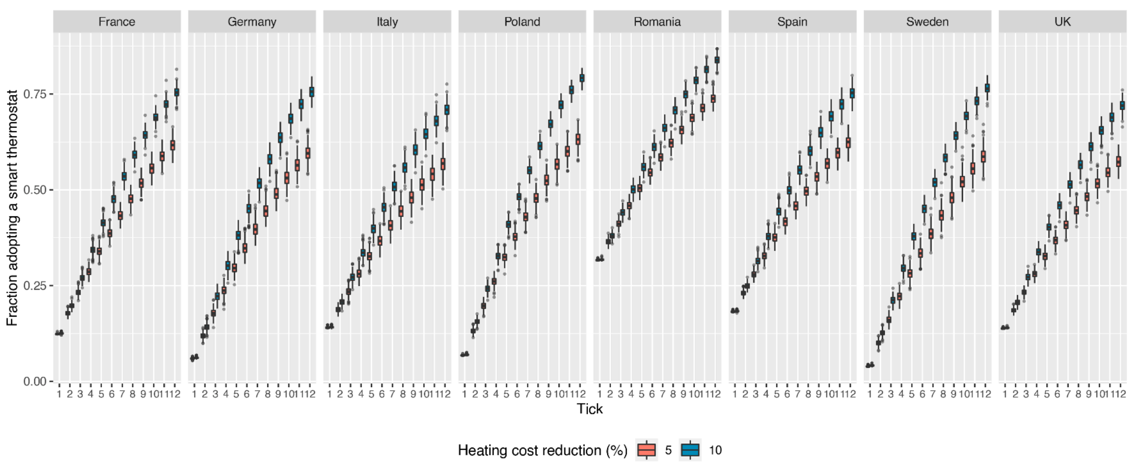

Fig. 2. Adoption of smart thermostats for no-policy scenario. Runs start in 2018 and end in 2030 (indicated with ticks 1-12). The scenarios distinguish between heating cost savings of 5% (in red) and 10% (in blue). Variation within a year for different runs are displayed as a box plot, where the box captures 50% middle values, the whiskers the other 50%, apart from outliers. Median is portrayed as a line in the box.

lowest income category in each country. For these 'benchmark' households, the coefficient associated with *price* is negative and statistically significant in all eight countries. Hence an increase in price (net of any subsidy) lowers the latent utility in equation (2) and also lowers the propensity to purchase a thermostat. The findings for *subsidy* and hence the effectiveness of a subsidy varies across countries. For half the countries in our sample, the coefficient is not statistically significant, implying that subsidies appear to have an effect on households' utility only through the decrease in net price. For Germany, Spain and the UK, it is negative, and for Romania it is positive. Thus, similar to the findings by Train and Atherton (1995) or Li et al. (2016) in related contexts, in these countries, subsidies have an additional negative or positive non-monetary effect on household utility. The findings for *savings* imply that, on average, participants from all eight countries value heating cost savings. Preferences for heating cost savings are particularly strong in Germany and Poland.

The coefficients associated with *recom_provider* and *recom_expert* are typically positive and statistically significant, suggesting that energy providers and independent energy experts are more reliable sources of advice than friends and colleagues (i.e. the baseline). To compare the effects of recommendations by energy providers versus energy experts, we carried out Wald tests. The results of these tests suggest that for Germany, Poland, and Sweden, the average participant preferred advice by experts rather than energy providers (at $p<0.05$). For the other countries in the study, the differences are not statistically significant.

In all countries, the coefficients for *remote* and *display* are positive and statistically significant, implying that participants value these technology attributes.

The interaction term between savings and households' scaled heating costs, *heat_x_savings,* is significant only in Sweden. Thus, for Sweden, but not for the other countries in our survey, we find evidence that respondents with higher heating costs value an additional 1% decrease in their heating costs more than households with lower heating costs. In addition, Table 2 suggests that preferences for smart thermostat attributes generally vary by income or age compared to the benchmark group, but there is substantial heterogeneity across countries.

3.2. ABM simulation results

We first present country-specific inputs for the simulations taken from the general survey (section 3.2.1). In a second step, we show the findings of a base simulation, for which no policy is assumed to be in place (section 3.2.2). In the next steps, we present the findings for the two policy simulations, i.e. the subsidy (section 3.2.3) and recommendations by independent energy experts and energy providers (compared to recommendations by friends only) (section 3.2.4).

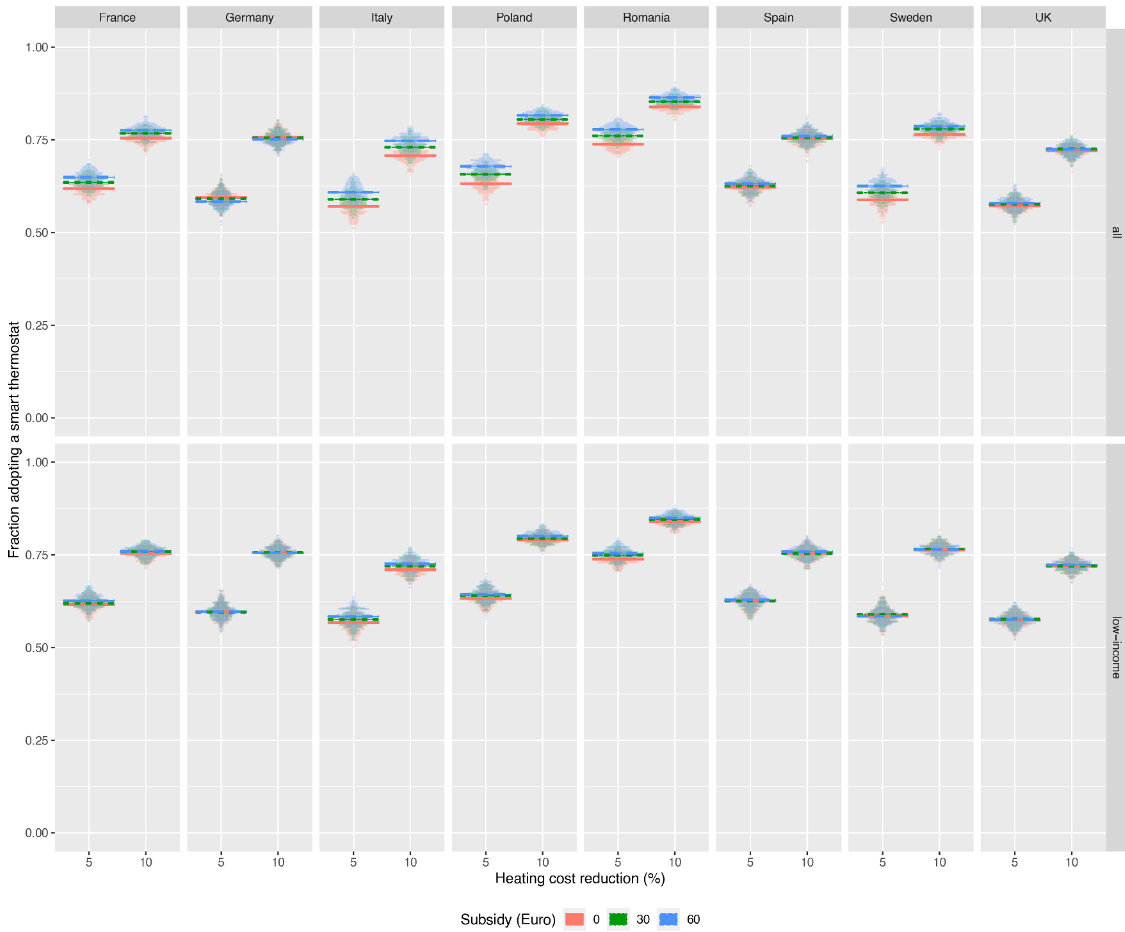

Fig. 3. Adoption of smart thermostats in 2030 for subsidy scenario. Top: all households receive subsidy; bottom: only low-income households receive subsidy. Median adoption rates are shown as horizontal lines. Spread is indicated by width of the shaded areas. The red non-dashed line refers to 10% heating cost savings. The blue dashed line depicts heating cost savings of 5%.

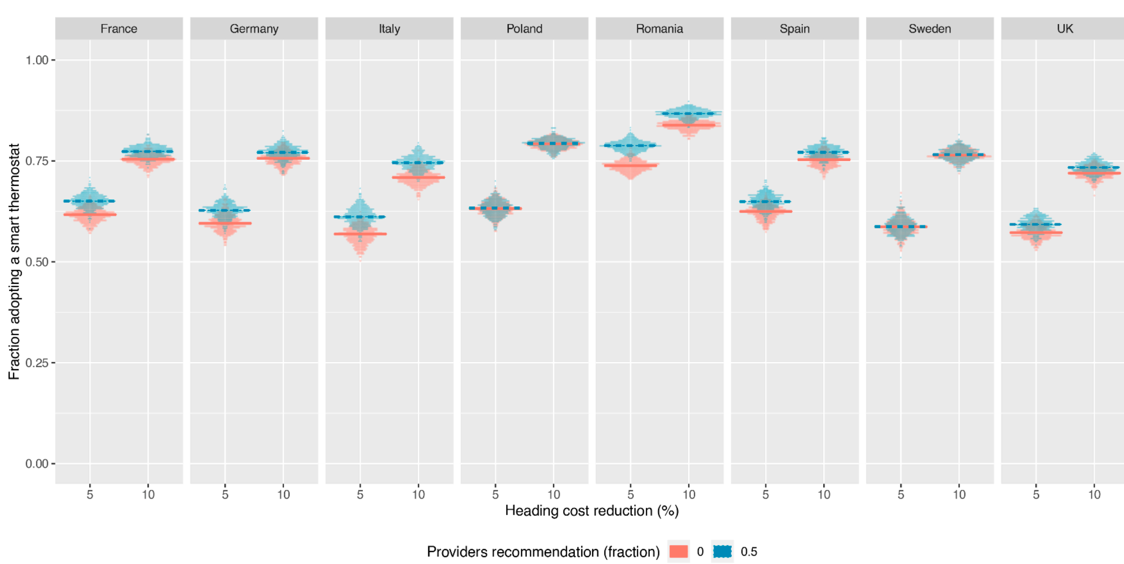

Fig. 4. Adoption of smart thermostats in 2030 for the provider recommendation scenario. Median adoption rates are indicated by horizontal lines. Spread is indicated by width of shaded areas. Red non-dashed line refers to no recommendation. Blue dashed line depicts 50% of smart devices are recommended by energy providers.

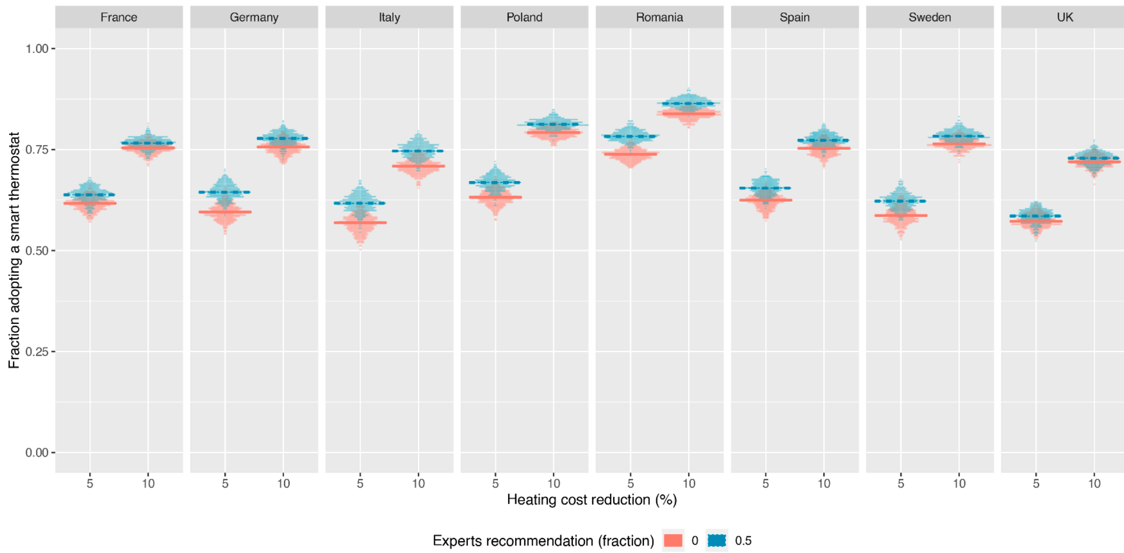

Fig. 5. Adoption of smart thermostats in 2030 for the expert recommendation scenario. Median adoption rates are indicated by horizontal lines Spread is indicated by width of shaded areas. Red non-dashed line refers to no recommendation. Blue dashed line depicts 50% of smart devices are recommended by providers.

3.2.1. *Country-specific information*

Table 3 presents information on the means and standard deviations of key household-level variables that are used in the simulation. This data is obtained from the general survey as described in section 2.1.1., and includes information on all survey participants, i.e. not only on those that were (randomly) chosen to participate in the thermostat DCE.

For age, countries are rather similar in terms of means and standard deviations, but the share of elderly (i.e. at least 55 years of age) varies between 13% for Romania and 26% for the UK. Similarly, the share of low-income households, i.e. those eligible for a subsidy in the subsidy policy scenario, varies considerably across our country samples, ranging from 23% for Poland to 45% for the UK.

The share of households that reported to have already adopted a smart thermostat in the year the survey was conducted (2018) varies substantially between countries, with low adoption rates of 3 to 7% in Germany, Poland and Sweden, medium adoption rates of 13 to 18% in France, Italy, Spain and the UK, and high adoption rates of 31% in Romania. These figures imply considerable heterogeneity in the starting position across countries, which will affect the path of smart thermostats adoption in the simulations.[16]

The descriptive statistics on heating costs suggest that heating costs also vary substantially across and within countries, reflecting heterogeneity in benefits of smart thermostat adoption. Differences in heating costs between countries may be explained by differences in the general climate, in typical heating technologies and in prices of the respective energy carriers. Differences within countries reflect heterogeneity in building and heating infrastructure and heating behaviour.

Finally, the number of options for devices that households typically consider also vary between countries - from around 6 for France, Germany and Spain, to 10 to 12 for the other countries - and within countries. These figures suggest considerable heterogeneity in the number of thermostats that households consider when they replace a thermostat.

3.2.2. *No-policy scenario*

Results of simulating the diffusion of smart thermostats in the *no-policy scenario* appear in Fig. 2 for each country. We distinguish two cases. The top (bottom) row shows the results for the 5%-case (10%-case) where the adoption of a smart thermostat is assumed to lower heating costs by 5% (10%). The expected adoption rates are presented per country per simulated year between 2018 and 2030, labelled as ticks 1-12. Because simulation runs with the same settings lead to varying adoption rates, we present the findings as box plots per simulated year: the median is shown as the horizontal bar in the box, the box contains 50% of the adoption rates simulated for that country in that particular year, the whiskers represent all other values that are not considered to be outliers.

The median and mean adoption rates differ across countries as well as their spread. In general, the expected rate of adoption of smart thermostats in 2030 is high. In comparison, the market of home energy management technologies in the EU is expected to grow annually at a rate of 10% (Guidehouse, 2020, p. 107). For the 5%-case (10%-case), this rate ranges from 55% (71%) in Sweden to 78% (86%) in Romania. In general, Romania and Poland exhibit the highest expected adoption rates in 2030, ahead of Germany, France, Sweden and Spain. The UK and Italy have the lowest expected adoption rates. These different rates reflect differences across countries (i) in preferences such as the valuation of heating cost savings (e.g. as presented in section 3.1); (ii) in the initial conditions such as the share of smart thermostats owned in 2018 leading to positive feedback effects through the social network (as presented in section 3.2.1); (iii) in the interaction of valuation and initial conditions such as differences in valuation by socio-economic groups; and (iv) in the number of options households consider when purchasing a thermostat. The adoption rates shown in Fig. 2 result from the combinations of these factors.

To illustrate the relative importance of these effects, we conducted additional simulations. To explore the role of the initial conditions, we ran an additional *no-policy scenario* simulation where we set the share of households who had adopted a smart thermostat in 2018 at zero in all countries (see Fig. C.1 in Appendix C). Comparing Fig. C.1 with Fig. 2 suggests that the high adoption rates in 2030 in Romania are mainly driven by the high initial adoption rates in 2018 and hence positive network effects. In contrast, the high adoption rate in Poland in 2030 can be explained by strong preferences for smart thermostat attributes such as net price, heating cost savings and remote control and display features (see Table 2). To explore this, we ran an additional simulation where we set all coefficients of the utility function for Poland to the averages of the other seven countries and compared the outcome (see

[16] For some countries - notably Romania - the self-reported adoption of smart thermostats appears high. Because of lack of publicly available data - information on smart thermostats is typically subsumed under home energy management system (HEMS) technologies (e.g. Guidehouse, 2020) – we cannot compare the numbers based on self-reports with those from actual adoption.

Fig. C.2 in Appendix C) with Fig. 2. Finally, the relatively low adoption rates of Italy and the UK may be explained by relatively weaker preferences for heating cost savings in these countries. Indeed, when we replace the coefficient associated with heating cost savings in Italy and the UK by the average value of these coefficients in the other six countries, adoption rates of smart thermostats in 2030 in Italy and the UK are similar to those of the other countries (see Fig. C.3 in Appendix C for the 5%-case).

From the differences across and within countries in Fig. 2 we observe that expected heating cost savings are an important driver of adoption. Mean adoption rates in 2030 are 10-20 percentage points higher in the 10%-case than in the 5%-case. This finding can be explained by the DCE results presented in Section 3.1. Accordingly, the coefficients associated with *savings* in Table 2 are statistically significant and large for all countries, suggesting that households care about heating cost savings.

For Romania, the difference in the median values between the 5%- and 10%-cases is relatively small because heating cost levels are relatively small (see Table 3), and the adoption rate is generally high. Hence a difference of 5 percentage points in heating cost savings does not translate into substantial monetary amounts. In comparison, the difference in adoption rates between the 5% case and the 10% case is particularly large in Germany, Poland, and Sweden where average heating costs and participants' valuation of heating cost savings are both high (see Table 2 and Table 3).

Finally, we note that – even without a subsidy or recommendations provided by energy experts or energy providers – the rates of smart thermostats adoption are quite high in 2030 in most of the countries in our sample. In addition to participants' high valuation of heating cost savings, these large rates are driven by assumptions made in the ABM about the average lifetime of thermostats (10 years) and the composition of consumers' consideration set when they purchase a new thermostat. These assumptions imply for instance that smart thermostats (and recommendations) are visible in the shops.

3.2.3. Subsidy policy scenario

Fig. 3 shows the adoption rates (median values and spread) in 2030 for each country when subsidies are implemented, and how these rates vary by subsidy eligibility and heating cost savings. The effects of subsidies are shown within each column for subsidy levels of 0, 30 and 60 euros per smart thermostat. In the rows, the target group for the subsidy is varied. The top part (bottom part) shows the results of the simulations when all households (only low-income households) are eligible to receive a subsidy. The effects of the subsidy depend on participants' valuation of the net price, and on potential negative or positive non-monetary effects associated with receiving a subsidy (see Table 2).

We first discuss the findings for the scenario where all households are eligible to receive a subsidy. Because in most countries adoption is already high without a subsidy, the impact of a subsidy is rather modest and the share of free riders is substantial. We find that subsidies offered to all households have the largest impact in France, Italy, Poland, Romania, and Sweden, where they increase adoption rates by 1-3% points per 30 euro increase in the subsidy in 2030. As can be seen in Table 2, for these countries the effect of a subsidy on the net price is not weakened by a countervailing non-monetary effect. In comparison, the effect of a subsidy is rather modest in Germany, Spain, and the UK. For these countries, the effect of a subsidy on the net price is offset by a negative non-monetary effect (see coefficient on *subsidy* in Table 2). Possibly, households in these countries perceive a subsidy as a signal for low quality of those devices (similar to Li et al. (2016)).

We note that in general, the effect of a subsidy on adoption is stronger when smart thermostats lower heating costs by 5% rather than 10%. Larger cost savings imply larger adoption rates in the *no-policy scenario*, and hence more free riding.

As illustrated in the lower part of Table 3, the impact of subsidies that are only offered to low-income households on the adoption of smart thermostats is modest in all countries. Because fewer households are eligible for the subsidy (between 24% and 45% of the households, see Table 3) subsidies targeted at low-income households are less effective. In addition, for Sweden, low-income households exhibit a larger negative non-monetary effect for subsidies than high-income households (see coefficient on *lowinc*_x_*subsidy* in Table 2). On the other hand, subsidies targeted at low-income households may be more efficient in terms of energy savings obtained per euro of subsidy spent because free riding is lower.

3.2.4. Recommendation policy scenarios

The effects of recommendations by energy providers and independent energy experts (compared to recommendations by friends or colleagues) on smart thermostat adoption rates are shown in Fig. 4 and Fig. 5.

For the *provider recommendation scenario,* we observe an increase in adoption rates of 3-5% points compared to the *no-policy scenario* for most countries. For some countries (e.g. France, Germany, and Spain), these effects are somewhat larger in the 5%-case than in the 10%-case because participants in these countries value energy costs savings relatively highly which translates into larger adoption rates in the *no-policy scenario*. In comparison, provider recommendations have no effects in Poland and Sweden because our DCE analysis did not find recommendations by energy providers to differ from recommendations by friends or colleagues in these countries (see Table 2).

For the *expert recommendation scenario,* Fig. 5 shows an increase in adoption rates compared to the *no-policy scenario* for all countries. As expected from the results of the DCE, compared to the *provider recommendation scenario*, the size effects are large for Germany, Poland, and Sweden, and similar for the other countries. Likewise, the impact of expert recommendations appears somewhat larger in the 5%-case than in the 10%-case.

4. Conclusions

In this paper, we link findings from a multi-country demographically representative DCE on the adoption of smart thermostats with an ABM (EMLab-Consumer) in a methodologically consistent way. Therefore, we did not have to use additional (ad-hoc) assumptions to parameterize agents' utility functions, i.e. the weights associated with particular technology attributes or policy variables, which ultimately govern technology choice and the diffusion of a technology. The empirical foundation of our ABM is further strengthened by integrating additional information (e.g. on the technology stock, heating costs, socio-demographics, and decision process). Most notably, our findings for the DCEs highlight the importance of allowing for heterogeneity in preferences within and across countries when parameterizing ABM models. Allowing preference parameters to vary by socio-demographic factors such as age and income partially captures this heterogeneity. These findings challenge the practice of transferring survey-based findings obtained for one country to parameterize a model for another country.

A simulation of the diffusion of smart thermostats in eight European countries until 2030 with the EMLab-Consumer model suggests that smart thermostats will quickly diffuse in most countries in our sample. The simulations further illustrate the importance of allowing for within- and between-country heterogeneity in preferences for technology attributes such as the valuation of heating cost savings, and in responses to policies such as subsidies, or recommendations by independent energy experts. Further, social interactions reinforce differences between countries in the technology stock in the starting year, in particular for a new technology like a smart thermostat. While we find that subsidies moderately accelerate the diffusion of smart thermostats, they are less effective in countries with a large stock of smart thermostats in the starting year, and when smart thermostats lead to a strong reduction in heating costs (in our case of 10% versus 5%). In these cases, adoption of smart thermostats is high even without a subsidy mainly because of positive social interaction effects and because households strongly value heating costs savings. These results also point to the importance of technological progress that may lead to substantial savings in heating costs. Our simulations further suggest that targeting subsidies at particular socio-economic groups (in our case low-income households) may slightly mitigate such free-riding effects. Finally, our policy simulations further imply that recommendations by energy providers or by energy experts accelerate the diffusion of smart thermostats compared to recommendations by peers.

In this study, we explore a hard link between a DCE and an ABM for a particular technology, a given set of technology attributes and policies and thereby allowing agents' valuation of attributes and policies to vary by age and income. A similar methodology could be applied to model the diffusion patterns of other novel household energy technologies or services. Similarly, in our context, additional or other attributes relevant for household adoption of smart thermostats could be included such as environmental benefits (e.g. lower CO_2-emissions), brand, or customer ratings of smart thermostats. Likewise, preferences could be varied by other socio-demographic factors such as gender or education and by regional differences within countries. Furthermore, DCEs may also be employed to examine barriers to energy efficiency. For example, the well-known landlord-tenant problem could be captured by splitting the samples between dwelling owners and renters, or by interacting an ownership dummy with the attributes in the econometric estimations of the DCE. In principle, DCEs could also be employed to analyse household preferences for owning or renting energy technologies such as heating systems or large household appliances (see Schleich et al., 2021). Finally, DCEs would allow estimating the role of behavioural factors like individual time or risk preferences for household adoption of technologies which may then be integrated into ABMS.

While hard-linking DCEs with an ABM to study the diffusion of smart thermostats in a multi-country setting allowed for interesting insights, the approach is subject to limitations. One important caveat is the hypothetical bias inherent in DCEs (e.g. Hensher, 2010). To mitigate the hypothetical bias in this study, we only used those choices in our analyses where participants indicated in a follow-up question that they would likely make the same choice in a real purchase situation. Further, it is only possible to establish a hard link for the product or service attributes that can be studied well via DCEs. For example, in our context, it would be challenging to directly capture in a DCE the role of data privacy concerns, perceived loss of comfort, transaction costs, or lack of information related to the adoption of a smart thermostat. Similarly, it would be difficult to capture the (perceived) quality of recommendations via a DCE. To avoid cognitive overload and to limit task complexity, only a limited number of attributes can be included in a DCE. Therefore, researchers may inadvertently neglect relevant attributes in DCE designs.

Next, and akin to other studies integrating survey-based data into models, our simulations until 2030 implicitly assume that agents' preferences do not change over this period. We also assume that preferences of laggards and early adopters of smart thermostats are identical.

Moreover, our simulation results depend on self-reported data such as whether households had a smart thermostat installed in 2018. Hence, our data may suffer from social desirability bias. Likewise, households may not have been able to correctly identify whether their thermostat was indeed a smart thermostat. If actual rates of adoption of smart thermostats in the initial year were lower than assumed, our simulations would have overstated the diffusion of smart thermostats for countries with strong network effects.

Further, our approach did not model the relation between consumers, retailers and technology providers. For example, retailers could employ adaptive marketing strategies and respond to low sales volumes with additional promotion measures. Similarly, we did not include a government agent, who could endogenously adapt policy. For example, a cost-minimizing government could lower the subsidy rate over time to limit free riding.

Despite these limitations, we believe our modelling approach and policy simulations help to better understand the effects of different mechanisms and preference heterogeneity on the diffusion of a novel energy technology like smart thermostats.

CRediT Author Statement

Emile Chappin: Conceptualization, Methodology, Investigation, Validation, Visualization, Writing - Original draft preparation, Writing - Reviewing and Editing. **Joachim Schleich:** Conceptualization, Investigation, Writing - Original draft preparation, Writing - Reviewing and Editing. **Marie-Charlotte Guetlein:** Formal Analysis, Investigation, Writing - Reviewing and Editing. **Corinne Faure:** Investigation, Writing- Reviewing and Editing. **Ivo Bouwmans:** Conceptualization, Writing - Reviewing and Editing.

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Appendix A

Instructions of the discrete choice experiment

The instructions used in the DCE are presented below. Fig. A.1 shows a choice card as used in the DCE and Fig. A.2 shows the framing used in the DCE.

Scenario 1

Which heating control device would you prefer?

	Option A	Option B
Heating bill	5% less	5% less
Remote temperature control	No	Yes
Display of changes in energy consumption	Yes	No
Recommendation	By friends or colleagues	By independent energy experts
Purchase price	£210	£270
Subsidy	£0	£60

	Option A	Option B
I prefer:	◉	○

How likely would you be to buy your preferred choice if it was available?

Very unlikely	Somewhat unlikely	Somewhat likely	Very likely
○	○	○	○

Fig. A.1. Example of a choice card shown to respondents in the DCE in the UK.

"Heating control devices are devices that **allow users to control the temperature of their home throughout the day**, for example by setting a different temperature at night. Moreover, some of those devices can be **connected to the Internet** and allow users to easily **adjust the temperature remotely**, for example by using a smartphone.

Example of a smart heating control device connected to the Internet using the home Wi-Fi network:

On the following pages, we will describe different heating control devices. We would like to know **which heating control device you would choose, if you were making a purchase and these were your only options.**"

Fig. A.2. Framing used to introduce the DCE in the UK.

Appendix B

Smart thermostat data

Table B.1 shows the smart thermostats used in the ABM.

Table B.1
Data on smart thermostats.

ID	Name	Price (in euros)	Remote temperature control	Display of changes in energy consumption
1	futurepowerp1monitor	100	No	No
2	smartmeterdashboard	19	No	No
3	energiemanageronline	31.4	Yes	Yes
4	cemmbasic	179.3	No	No
5	iungo	189	No	No
6	energylinkhomewizard	279	No	No
7	Smappeegas & water	450	No	No
8	youlessenergymonitor	79	No	No
9	MEMo2wire	623	Yes	No
10	huisbaasje	133	No	No
11	mijnwoning.nl	0	No	No
12	smartdodosslimmemeteruitlezer	0	No	No
13	toon	383	Yes	Yes
14	spiderconnect	299	Yes	Yes
15	slimmemeterwifiadapter	86.75	Yes	No
16	milo2wire	175.45	Yes	Yes
17	bokslive	110	No	No
18	oxxioapp	0	No	No
19	slimmemeterportal.nl	0	No	No
20	beeclear	99	No	No
21	enelogicpremium	117	No	No
22	maxem	634	No	No
23	aurumenergieapp	99.95	No	No
24	smappeenergy	229	No	No
25	enelogicbasis	0	No	No
26	smappeesolar	349	No	No
27	essentthuisapp	49	Yes	Yes
28	enelogicpremium	38	No	No
29	engieeapp	0	Yes	No
30	umeter	0	No	No
31	optosense	193.9	No	No
32	slimmemeteruitlezen.nl	40	No	No
33	trioIIenergiedisplay	99.95	No	No
34	smappeeplus	599	No	No
35	powersense	193.9	No	No
36	iunoglite	109	No	No
37	mijnenergieinzicht	0	No	No
38	mijnhuisonline	336	Yes	No
39	plugwisesmilep1	99	No	No

Source: Adapted from https://www.energieverbruiksmanagers.nl.

Appendix C

Additional simulation results

Figs C.1 to C.3 provide additional simulation results checking the validity of some of the key results. Fig. C.1 shows the adoption of smart thermostats for the *no-policy scenario* assuming adoption rate of zero in 2018 in all countries. Figs C.2 and C.3 show additional results for specific countries using modified utility coefficients for the 5% heating cost savings case. In Fig. C.2, the utility of price, heating cost savings and of remote and display functions were replaced by the respective averages of the other seven countries for Poland. In Fig. C.3, the utility of heating cost savings was replaced by the average of the other six countries for

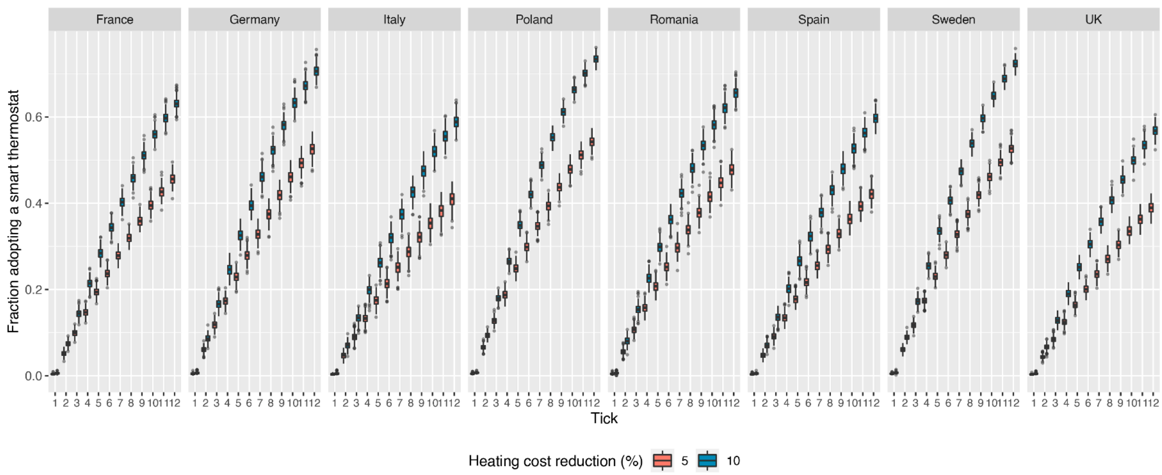

Fig. C.1. Adoption of smart thermostats for no-policy scenario assuming adoption rate of zero in 2018 in all countries.

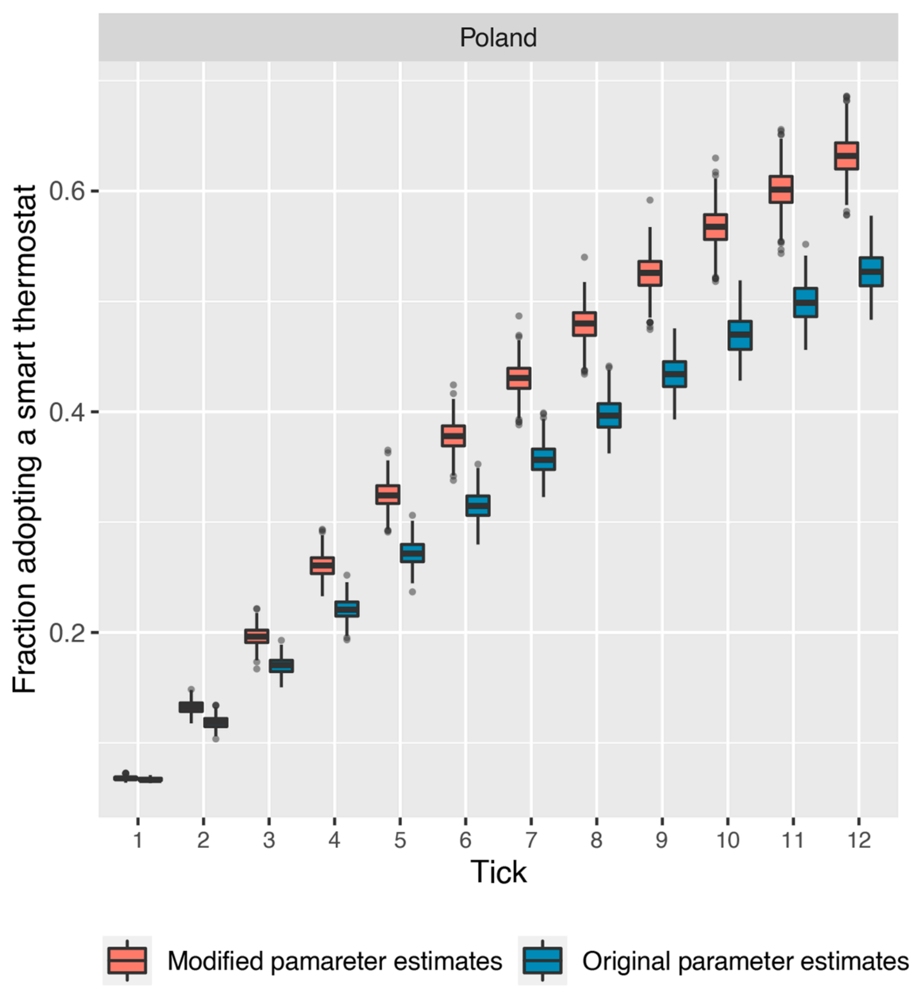

Fig. C.2. Adoption of smart thermostats in Poland for original (green) and alternative (red) specification of the utility function.

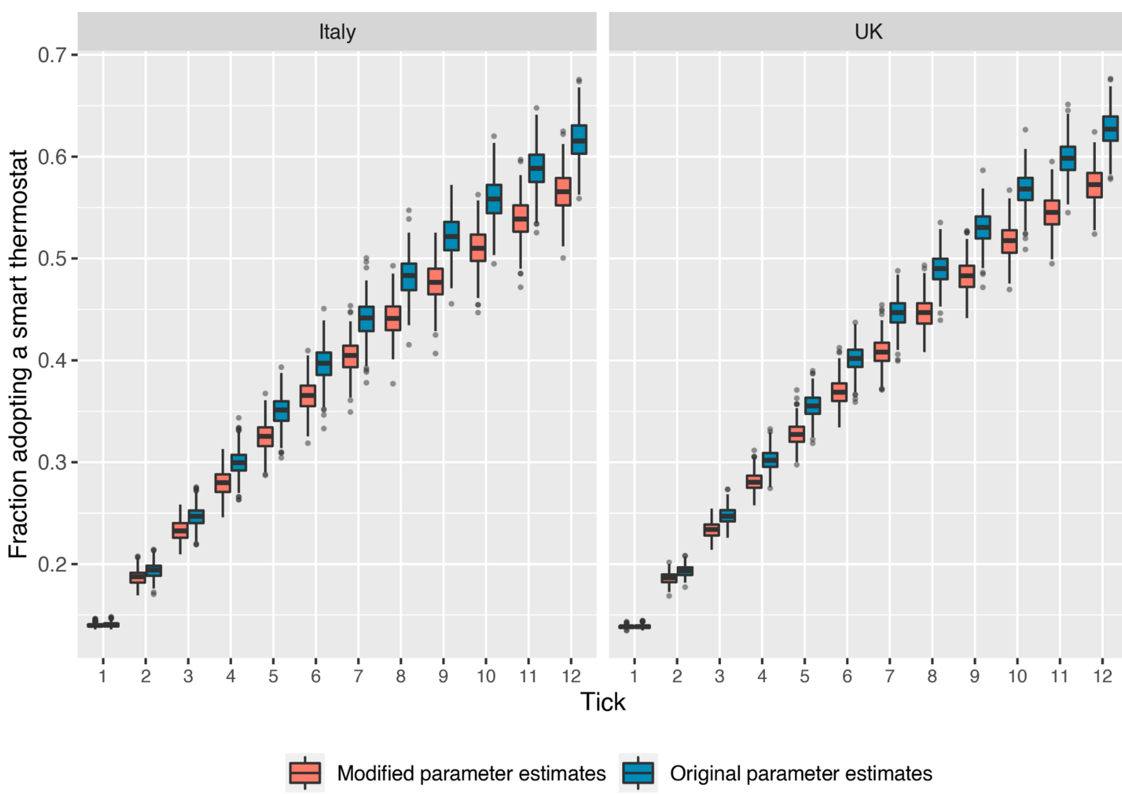

Fig. C.3. Adoption of smart thermostats in Italy and the UK for original (green) and alternative (red) specification of the utility function.

the UK and Italy.

Appendix D

ODD+D Protocol for EMLab-Consumer (smart thermostat version)

Following Müller et al (2013), Table D.1 presents the ODD+D (overview, design concepts and details including human decision making) protocol - an established standard for describing ABMs that include human decision-making protocol for the model EMLab-Consumer (specific to smart thermostats simulations).

Table D.1
ODD+D for the model EMLab-Consumer, specific to smart thermostat simulations.

	Outline	Guiding questions	EMLab-Consumer
Overview	I.i Purpose	I.i.a What is the purpose of the study?	We simulate the diffusion of smart thermostats in eight European countries until 2030 (i.e. description); we directly integrate findings from demographically representative surveys using DCEs in the same countries. We simulate the effects of subsidies and recommendations by energy providers and experts compared to recommendations received from peers. The model EMLab-consumer has been developed to also simulate other devices (fridges, heating systems, etc.); some of the implemented functionality does not apply to thermostats. Such additional functionality includes: house-/household-specific restrictions for devices, electricity consumption of devices, manufacturer improvement of the energy efficiency of devices, shops introducing new appliance models and taking old models from their stocks, various policy variables such as energy labels. Features that do not apply are not included in the description below.
		I.ii.b For whom is the model designed?	Researchers and energy policy analysts/policy-makers.
	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	Households including their homes with appliances, the government as a policy-maker, shops that sell appliances, manufacturers that develop appliances
		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterized?	Households: age (years), income, current thermostat, yearly heating costs (€/year), number of options considered while replacing, utility function. Thermostats: price, whether they are smart or not (represented as label A vs B), whether they can be remotely controlled, whether they have a display. Shop: stock of appliances.
		I.ii.c What are the exogenous factors / drivers of the model?	Gas prices, policy variables, percentage of heating costs saved by

(continued on next page)

Table D.1 (*continued*)

	Outline	Guiding questions	EMLab-Consumer
			adopting a smart thermostat.
		I.ii.d If applicable, how is space included in the model?	Agents are scattered around at the start of the simulation in a 2D street-like orientation so they have neighbors that they can observe.
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	1 time step represents 1 year. The simulation runs for ticks 0-12, representing the years 2018-2030. One grid cell can host one house.
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	Policy specific interventions. Shops update their stock. Appliances break at the end of their lifetime. Households decide whether they want to replace still working appliances. Households replace broken appliances and appliances selected in 4. Households consume energy by using the appliances. Households pay for the energy they consume Decommissioned appliances are removed from the simulation The screen is updated. Proceed to the next tick; stop the simulation after tick 12.
Design Concepts	II.i Theoretical and Empirical Background	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?	Theory of Planned Behavior (Ajzen, 1985).
		II.i.b On what assumptions is/are the agents' decision model(s) based?	Utility theory for the replacement decision. The key purpose of this model is to integrate both representative survey results of households as well as mixed logit models that model the household's replacement of appliances.
		II.i.c Why is a/are certain decision model(s) chosen?	Because of the model purpose: to hard-link results from a survey and discrete choice experiment.
		II.i.d If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from?	Representative survey in 8 countries, and the results from a discrete choice experiment on thermostat purchase.
		II.i.e At which level of aggregation were the data available?	The survey data is at the household level. The results from the discrete choice experiment is at the population level, but includes heterogeneity with respect to

(*continued on next page*)

Table D.1 (*continued*)

	Outline	Guiding questions	EMLab-Consumer
			demographic properties (age, income) and includes standard deviations that enable varying data between households of the same group.
	II.ii Individual Decision Making	II.ii.a What are the subjects and objects of decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision making included?	Individual households decide on replacement of individual appliances in their homes.
		II.ii.b What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?	Rational choice (utility maximization).
		II.ii.c How do agents make their decisions?	Primarily on the basis of a utility function.
		II.ii.d Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?	No.
		II.ii.e Do social norms or cultural values play a role in the decision-making process?	No.
		II.ii.f Do spatial aspects play a role in the decision process?	Agents consider appliances that they observe from friends (in their social network which is generated at the start of the simulation, and includes households that are nearby in space).
		II.ii.g Do temporal aspects play a role in the decision process?	Appliances have a lifetime, so the trigger for replacement is mainly coming from appliances that break down.
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?	Standard deviations for the utility functions represent uncertainty in the agent behavior: agents from the same group all have slightly different utility functions. Utility coefficients differ only for standard deviations that were statistically significantly different from 0. Furthermore, the utility function provides the relative probabilities for purchasing new appliances: an appliance with a higher utility has a higher chance of being adopted than one with a lower utility (see equations later in this document).
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time	No.

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Table D.1 (*continued*)

	Outline	Guiding questions	EMLab-Consumer
		as consequence of their experience?	
		II.iii.b Is collective learning implemented in the model?	No.
	II.iv Individual Sensing	II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?	Exogenous: households know all exogenous variables, they know energy prices, they know whether subsidies are relevant, who recommends an appliance, whether an appliance fits the home. Endogenous: households sense what appliances are in store, whether appliances are broken. No erroneous processes.
		II.iv.b What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?	Agents observe appliances of others, so their decisions co-evolve. No erroneous processes.
		II.iv.c What is the spatial scale of sensing?	Local and social network. Shops in the vicinity.
		II.iv.d Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?	Modelled explicitly in the set of options agents consider in their replacement logic.
		II.iv.e Are costs for cognition and costs for gathering information included in the model?	Only implicitly through recommendations by energy experts and providers (the value of lowering high-quality information).
	II.v Individual Prediction	II.v.a Which data uses the agent to predict future conditions?	Assuming constant energy prices and appliance prices.
		II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?	None.
		II.v.c Might agents be erroneous in the prediction process, and how is it implemented?	Their energy costs may be erroneous, as the model assumes constant energy prices. They also do not anticipate replacement of other appliance types, which affects the myopic foresight in simulations where multiple appliance types are included.
	II.vi Interaction	II.vi.a Are interactions among agents and entities assumed as direct or indirect?	Direct interactions amongst household agents and between households and shops, indirect interactions with manufacturers and governments.
		II.vi.b On what do the interactions depend?	Spatial distance and network.
		II.vi.c If the interactions involve communication, how are such communications represented?	Interactions between households are not using communication; only based on observations.

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Table D.1 (*continued*)

Outline	Guiding questions	EMLab-Consumer
	II.vi.d If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?	The social network is scale free, generated at the start of the simulation and static during the simulation.
II.vii Collectives	II.vii.a Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?	No. (There are utility terms that are specific for socio-demographic groups).
	II.vii.b How are collectives represented?	N/A.
II.viii Heterogeneity	II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?	Yes, in their demographic properties according to the survey, the properties of their homes and appliance and in their utility functions.
	II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?	The utility function takes into account heterogeneity between various socio-economic groups and standard deviations within the group. (The utility coefficients in the utility function differ for variables for which statistically significant standard deviations were found from the discrete choice experiment.)
II.ix Stochasticity	II.ix.a What processes (including initialization) are modeled by assuming they are random or partly random?	Some of the missing data, interpolation of data that is incomplete (specific number from a range which was part of a survey question). The current age of the appliances is random between 0 and the lifetime, the order in which agents decide on replacement, the generated social network, the utility weighted probability in the replacement decision (see below).
II.x Observation	II.x.a What data are collected from the ABM for testing, understanding, and analyzing it, and how and when are they collected?	Through NetLogo's textual reporting function, all functions were tested during the development. The initialization code contains error notifications when input data is incomplete or erroneous. All settings, and data are stored in separate text files and there is a default settings file. All key model outputs are collected in runs in NetLogo behavior space experiment, and processed with R to visualize main results, including spread and aggregate statistics.

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Table D.1 (*continued*)

	Outline	Guiding questions	EMLab-Consumer
		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)	Diffusion patterns, specific to countries, socio-economic groups, policy settings, including spread between results.
Details	II.i Implementation Details	III.i.a How has the model been implemented?	Netlogo.
		III.i.b Is the model accessible and if so where?	The model is published open source. It is available through http://emlab.tudelft.nl.
	III.ii Initialization	III.ii.a What is the initial state of the model world, i.e. at time t=0 of a simulation run?	Each household in a country in the survey is represented as one agent.
		III.ii.b Is initialization always the same, or is it allowed to vary among simulations?	The simulation runs one country at a time; policy variables affect the simulation runs.
		III.ii.c Are the initial values chosen arbitrarily or based on data?	Based on data.
	III.iii Input Data	III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?	Based on survey results from the EU H2020 CHEETAH project survey (https://www.briskee-cheetah.eu/cheetah/) and Eurostat energy price data.
	III.iv Submodels	III.iv.a What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'?	Government applies policy-specific interventions. For subsidies: government alters the prices according to the subsidy level that consumers pay for eligible devices. This can be target-group specific (only elderly or only low-income households). For recommendations, each device eligible for recommendations may be flagged as recommended. For restrictions, some devices may be taken out of stores (not applicable to thermostats). Shops update their stock (new or improved appliances are included, but this is not applicable to thermostats, which are assumed to be available throughout the simulation). Appliances break at the end of their lifetime (which is determined when appliances are created. The actual lifetime is based on the expected lifetime and a standard deviation. Thermostat lifetimes are assumed to be 10 years; they vary with a standard deviation of 3 years. Households decide whether they want to replace still working appliances, this is done randomly for 1% of the households. Households replace the

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Table D.1 (*continued*)

Outline	Guiding questions	EMLab-Consumer
		appliances marked in step 4 and all broken appliances according to the scheme in the main article (Fig. 1). First, they visit a shop that matches their selection. They first select all relevant options from the shop, which becomes their longlist of options. They add thermostats of some of their neighbors and friends to this longlist. From this list, they draw, at random, a shortlist (sized as the typical number of options they consider) and this becomes the consideration set. For each of the thermostats in this consideration set, they apply their utility function to determine their utility. Utility functions stem from the mixed logit models. For smart thermostats in particular, (see Equation 1 in the paper), this utility function includes parameters regarding the thermostat (price, display, remote access), households (especially elderly and/or low-income), and policy (subsidy level) and further assumptions (heating cost savings). Finally, households select one thermostat out of the set on the basis of a utility-weighted probability. Purchasing probabilities are calculated according to Equation 2 in the paper, where higher utility translates to a higher chance of purchase. Old appliances are marked decommissioned. Households consume energy by using the appliances. A smart thermostat is assumed to lead to particular heating savings because households are able to observe their heating consumption. Households pay for the energy they consume for their appliances (not directly applicable to smart thermostats, but for heating systems, fridges, and so on.). Decommissioned appliances are removed from the simulation for performance reasons. The screen is updated.

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Table D.1 (*continued*)

Outline	Guiding questions	EMLab-Consumer
		Proceed to the next tick, until the simulation is stopped.
	III.iv.b What are the model parameters, their dimensions and reference values?	For *all main simulation parameters*, data is coming from country-specific survey parameters. This process is explicitly coded, including the set of parameter names and imputation of missing data. Reference values for the parameters below are in parentheses. Other *general model parameters* are the number of shops that households visit (all) and parameters about how the social network is generated and how this affects the purchase decisions: minimum network size (3), number of appliances of friends (in the network) that households consider (5), number of appliances of neighbors that agents consider (5), the radius that households use to find neighbors (2) and, finally, the number of friends' or neighbors' appliances that households will add to their consideration set (3). For the simulation of *thermostats* in particular, policy variables (which are otherwise turned off by default): the level of a subsidy (reference € 0), which households are eligible for the subsidy (all households), the fact that only smart thermostats (label A) are eligible for subsidies, the percentage of heating costs reduction due to having a smart thermostat (reference value 10%), and whether smart thermostats can also by replaced by regular thermostats (off). Other model parameters are specific to other appliances (e.g. appliance improvements and price developments). A number of switches are included for testing functionality.
	III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?	The model was developed in the context of the EU H2020 project CHEETAH (https://www.briskee-cheetah.eu/cheetah/); parametrization was developed in communication with

(*continued on next page*)

Table D.1 (*continued*)

Outline	Guiding questions	EMLab-Consumer
		various project partners, presenting preliminary model versions and results.

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