# Transition to low-carbon economy: Assessing cumulative impacts of individual behavioral changes

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## ABSTRACT

Changing residential energy demand can play an essential role in transitioning to a green economy. Environmental psychology suggests that behavioral changes regarding energy use are affected by knowledge, awareness, motivation and social learning. Data on various behavioral drivers of change can explain energy use at the individual level, but it provides little information about implications for macro energy demand on regional or national levels. We address this challenge by presenting a theoretically-based and empirically-driven agent-based model to track aggregated impacts of behavioral changes among heterogeneous households. We focus on the representation of the multi-step changes in individual energy use behavior and on a quantitative assessment of their aggregated impacts on the regional level. We understand the behavioral complexity of household energy use as a dynamic process unfolding in stages, and explore the barriers for utilizing the full potential of a region for emissions reduction. We suggest a policy mix that facilitates mutual learning among consumers.

## 1. Introduction

Anthropogenic greenhouse gas (GHG) emissions continue to rise (UNEP, 2017). Keeping average global temperature below a critical limit of 1.5 °C above pre-industrial levels calls for ambitious emission reduction efforts. To reduce carbon intensity economies throughout the world rely on social and technological changes. The distributed nature of renewables, increasingly competitive costs of renewable technologies, and new developments in smart grids and smart homes further help energy consumers to become active players in this domain (EC, 2017). Prevailing social norms, which shape individual decisions and which are shaped by them, could be a response to global environmental problems (Nyborg et al., 2016). A need to understand the role of individuals in a transition to low-carbon economy, calls for quantitative analysis of behavioral changes with respect to energy use.

Residential energy use accounts for almost 24% of GHG emissions in Europe. Early assessments indicate that behavioral change alone can remove between 4% (McKinsey, 2009) and 5–8% (Faber et al., 2012) of the overall $CO_2$ emissions. Quantifying aggregated impacts of household behavioral change is, however, a challenging task. The quantitative tools to support energy policy decisions range from assessment of macro-economic and cross-sectoral impacts (Kancs, 2001; Siagian et al., 2017), to single sector analysis of costs and benefits (Kumar, 2016), and

detailed micro-simulation models for a specific technology (Bhattacharyya, 2011; Hunt and Evans, 2009). Yet, behavioral shifts among households are often modeled in a rudimentary way assuming a representative consumer (a group), a perfectly informed choice based on rational optimization, and instantly equilibrating markets. Going beyond a stylized representation of a perfectly informed optimizer requires a theoretically and empirically solid alternative. The growing body of empirical literature in social sciences (Abrahamse and Steg, 2009; Bamberg et al., 2015; De Groot and Steg, 2009; Poortinga et al., 2004; Wall et al., 2007) acknowledges complex behavioral processes among households who consider changes in their energy consumption and decide on related investments and use practices. A range of theories in environmental psychology consider attitudes, norms, perceived behavioral control, awareness and responsibility to be vital in the process of individual decision making regarding energy use (Abrahamse and Steg, 2009; Adnana et al., 2017; Karatasou and Santamouris, 2010; Onwezen et al., 2013). Importantly, these studies differentiate between intentions and actual changes in individual behavior, and highlight the role of awareness, information and social peer influence on this process (Abrahamse and Steg, 2011; Frederiks et al., 2015). Omitting these behavioral factors, which may serve as drivers or barriers, could be misleading when studying the role of the residential sector in a transition to a green economy.

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**Table 1**
Overview of energy-related behaviors in the housing sector.

| Energy-related behavioral changes | Examples | Last related factsheets |
|---|---|---|
| **1. Investment (Action 1)** | - Installing solar power system<br>- Installing thermal solar power system<br>- Roof/floor insulation<br>- Installing efficient appliances<br>- Installing smart meters | Abdmouleh et al. (2018)<br>Deng and Newton (2017)<br>Buchanan et al. (2016)<br>Rai and Henry (2016)<br>Buryk et al. (2015)<br>Ameli and Brandt (2015)<br>Rai and Robinson (2015)<br>Tran (2012)<br>Chappin et al. (2007) |
| **2. Energy conservation (Action 2)** | - Turn off extra devices<br>- Consciously use less electricity<br>- Run only full load washing machines<br>- Tolerate lower (higher) temperature in winter (summer) | Thøgersen (2017)<br>Amouroux et al. (2013)<br>Faber et al. (2012)<br>Mills and Schleich (2012) |
| **3. Switching a supplier (Action 3)** | - Switch conventional to green supplier<br>- Switch to greener supplier | He and Reiner (2017)<br>Rommel et al. (2016)<br>Yang (2014)<br>McDaniel and Groothuis (2012)<br>Tran (2012) |

Empirical data about various behavioral drivers of change is essential for understanding energy use choices at the individual level. Yet, it provides little information about implications for macro energy demand and for the corresponding emissions footprint on regional or national level. Proper aggregation methods are in demand. Agent Based Modeling (ABM) is a simulation approach to study aggregated dynamics emerging from actions of heterogeneous individual agents, which make decisions and interact with each other according to theoretical and data-driven rules. Boundedly rational agents, their potential to learn, and an ability to unfold a decision process in stages, allows ABMs to accommodate the complexity of human behavior in energy systems (Rai and Henry, 2016). ABM departs from using system-level equations explicitly representing the behavior of energy consumers, such as households, using a range of theories. This method is actively used in energy applications to study national climate mitigation strategies (Gerst et al., 2013), energy producer behavior (Aliabadi et al., 2017), renewable energy auctions (Anatolitis and Welisch, 2017), consumer adoption of energy-efficient technology (Chappin and Afman, 2013; Jackson, 2010; Palmer et al., 2015; Rai and Robinson, 2015), shifts in consumption patterns (Bravo et al., 2013), and changes in energy policy processes (Iychettira et al., 2017). ABM receives much attention currently in climate change mitigation discussions (Stern et al., 2016). Yet, many ABMs still either lack a theoretical framework (Groeneveld et al., 2017) or relevance empirical data, especially when studying energy-related behavior of households (Amouroux et al., 2013; Chappin et al., 2007).

This paper aims to quantitatively explore the impact of behavioral factors on the energy use of individual households and the aggregate dynamics of residential energy demand in a region., Its innovative contribution to the literature is threefold. Firstly, we extend individual energy demand modeling based on economic factors alone, by explicitly accounting for potential behavioral drivers and barriers in a formal model. Secondly, while acknowledging the importance of solid empirical behavioral data collected in harmony with recent findings in environmental psychology, the article introduces a simulation method that allows to aggregate individual behavioral and economic heterogeneity and captures dynamics in the aggregated regional trends looking beyond a snapshot of a survey. Thirdly, this article uniquely contributes to the growing body of literature on energy ABMs by focusing on the multi-step representation of individual energy use choices in a fully modeled energy market relying on theoretically and empirically-grounded agent rules. This combination of behavioral data collection via a survey with a simulation modeling allows us to address the main research question: how do different cognitive stages and psychological and social processes affect individual energy choices,

cumulative regional energy demand and corresponding $CO_2$ emissions?

The article proceeds as follows. By drawing on critical insights on behavioral change from environmental psychology, we illuminate the key factors of energy-related behavior (Section 2) and present the design and summary of our survey (Section 3.1). We apply ABM to assess the cumulative impacts of individual behavioral changes with respect to energy use, accounting for socioeconomic heterogeneity, psychological factors and social network influence (Section 3.2). While grounding the model in these psychological and economic micro-foundations, we focus our analysis on the emerging macro properties (Section 4). The latter include macro trends in the diffusion of energy related practices among households (investments in energy efficient technical means, conservation due to changes in energy use habits or switching among energy sources), aggregated changes in shares of renewable energy consumption and corresponding $CO_2$ emissions at the regional level. We argue that understanding the behavioral complexity of energy-related households' decisions as a dynamic process unfolding in stages, uncovers barriers for utilizing the full emissions reduction potential of a region and calls for a policy mix that facilitates mutual learning among consumers (Section 5).

## 2. Human energy-related decision process

There are a number of actions households may pursue individually which impact their energy footprint. We categorize them into three main types of energy-related behavioral changes (Table 1). A household could make an investment (Action 1): either large, such as in solar panels and house insulation, or small, such as buying energy efficient appliances (A++ washing machine or light bulbs). Alternatively, households may save energy by changing their daily routines and habits (Action 2): by adjusting their thermostat or by switching off the lights. Finally, households could switch to a supplier that provides green(er) electricity (Action 3).

Empirical studies in psychology and behavioral economics show that consumer choices and actions often deviate from the assumptions of rationality: there are persistent biases in human decision-making (Frederiks et al., 2015; Kahneman, 2003; Niamir and Filatova, 2016; Pollitt and Shaorshadze, 2013; Stern, 1992; Wilson and Dowlatabadi, 2007). It implies that people do not necessary pursue the 'optimal choice' even if it is economically beneficial for them to do so. Unfolding a decision-making process in stages may potentially reveal where different biases and barriers start to play a role and how they may impact a decision.

Environmental psychology reveals various behavioral factors that are essential for understanding individual energy use decisions.

Abrahamse and Steg (2009) study to what extent socio-demographic and psychological factors are related to the households' energy use and savings by applying Norm Activation Theory (NAT)[1] and Theory of Planned Behavior (TPB).[2] They argue that the NAT variables such as awareness and personal norms significantly add to the explanation of energy-related behavior, more than the TPB variables such as attitudes and perceived behavior control. In addition, they mention that different types of energy-related methods appear to be related to different sets of variables. Onwezen et al. (2013) also consider the NAT and TPB integrated framework in order to get better insights into the role of pride and guilt in pro-environmental behavior. Adnana et al. (2017) use the extended TPB in predicting consumers' intentions toward the adaptation of electric and plug-in hybrid electric vehicles. In their framework, the three core components of TPB – attitudes, subjective norms, and personal norms – are used. In addition they add some socio-demographic control variables to test their impact of intentions to adapt. Sarkis (2017) shows the importance of using behavior change and decision making models in illustrating consumers energy behaviors by comparing TPB and the Value Belief Norm theory. He argues that using any theoretically based framework to understand human behavior is inheritably linked to individual psychological variables – beliefs, norms and attitudes – which should be tested empirically. However, concrete studies of residential energy-related behavioral changes, verified by detailed empirical data, are rare (Bhushan et al., 2016; Stern et al., 2016).

Naturally, these various decision theories can be used in ABMs to go beyond the assumption of a rational optimizer with perfect information. However, only a few of ABMs in the energy and environmental domain employ them currently (Table 2).

Abrahamse and Steg (2009); Bamberg et al. (2007); Onwezen et al. (2013) have indicated that knowledge and awareness in particular play an important role in pro-environmental decisions. While its impact on individual responsibility and personal norms is discussed (Abrahamse and Steg, 2011), the influence of individual awareness on the diffusion of energy-efficient practices and cumulative reduction in emissions is rarely studied. ABM can be a unique tool in order to perform quantitative analysis of aggregative consequences of either lack or presence of individual knowledge and awareness. The NAT theory, originally developed by Schwartz (1977), aims to explain altruistic and environmentally friendly behavior. Personal norms are at the core of this theory, and are used to explain individual behavior. Personal norms are determined by two main factors: awareness and responsibility, while in turn they are influenced by subjective norms and perceived behavior control. In the NAT terminology, one should differentiate between personal norm, which is expectations that people hold for themselves, and subjective norms, which is the perceived social pressure to engage or not to engage in a behavior. The awareness indicates knowledge that choosing (or not) a specific behavior has certain consequences. The household feels responsibility for delivering a particular behavior when they are sufficiently aware, and are motivated by their environment (Abrahamse and Steg, 2009; Onwezen et al., 2013; Schwartz, 1977).

To be able to reach a decision to pursue a particular behavior (Box IV, Fig. 1), an individual first needs to be aware of a problem (Box I,

Fig. 1). A sufficient level of awareness then leads to understanding own individual responsibility, i.e. the consequences of own actions (Box II in Fig. 1). Subjective norms (that link Box I and II in Fig. 1) account for the perceived social pressure to engage or not to engage in a particular behavior, e.g. solar panel installation in a neighborhood could bring attention of households and raise their awareness, contributing to the feeling of responsibility. Subjective norms act as a mediating factor that either raises or suppresses individual awareness and feelings of responsibility. For instance, actions of friends and family, or neighbors could encourage an individual to pursue the same action, e.g. installing solar panels or changing daily energy use habits, which reduce households' energy consumption and, consequently, an electricity bill. When a household reaches a threshold of responsibility – implying that a person feels that her actions can make a difference- it assesses its perceived behavior control (the link between Box II-III). Perceived behavior control (PBC) characterizes the extent, to which performing a particular behavior is easy or difficult. PBC indicates whether it is in one's control to execute a particular action. Would it be difficult/easy to install a solar panel? Can I afford it? If one feels that she has a degree of control over it, she moves to another stage where personal norms (Box III) are assessed to prioritize among actions. Personal norms include any rules one may have created for herself beyond or outside the prevailing subjective norms (Box I-II). For instance, a person may feel good when using energy from a renewable source. It is a value or principle that morally obliges individuals to either pursue a behavior change or not.

## 3. Methodology

To investigate cumulative impacts of behavioral changes of households and their potential contribution to shifts in a regional residential energy demand, we integrate behavioral aspects of individual decision making into an energy market model. An extensive household survey and an empirical residential energy demand ABM, both grounded in the NAT framework (Fig. 1), form a solid basis for our analysis. Empirical behavioral rules for agents in the simulation model are derived using the data from the households survey carried out in the Navarre region of Spain in 2016 (Section 3.1). The Behavioral change in ENergy Consumption of Households (*BENCH*) agent-based model is designed to simulate the energy-related multi-stage decision making process in heterogeneous households, which differ in socio-demographic factors and climate-energy-economy preferences (Section 3.2). To reach any of the three decisions, household agents in *BENCH* go through a decision-making process, which includes several stages (Fig. 1) based on NAT. The architecture of the *BENCH* model follows its prototype: a stylized energy market ABM (Niamir and Filatova, 2015). Here we go far beyond that simple toy model by adding a multi-stage behavioral process of decision-making among households who consider energy-related decisions based on solid theoretical and empirical ground.

### 3.1. Household survey

Navarre is a province in northern Spain, and consists of 272 municipalities. Navarre is a European leader in its use of renewable energy technologies. In 2016 we ran a household survey over an extensive sample of respondents, N = 800 households, using an online questionnaire (Appendix A). We designed the survey based on the environmental psychology literature to identify potential factors of households' energy-related behavioral changes. Specifically, our household survey focuses on factors potentially affecting a decision-making process with respect to the three types of energy-related actions that households typically make: (1) investments to save or produce energy, (2) conservation of energy by changing consumption patterns and habits, and (3) switching to another energy source. The conceptual framework behind the survey based on the NAT (Section 2) assumes three main steps that lead to one of these actions: knowledge activation, motivation, and consideration (Fig. 2). In each step, several psychological factors (e.g. awareness, personal norms, feeling guilt), economical (e.g.

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[1] NAT is originally developed by Schwartz (1977), Normative Influences on Altruism1, in: Leonard, B. (Ed.), Advances in Experimental Social Psychology. Academic Press, pp. 221–279, to study altruistic and environmentally friendly behavioral. The theory assumes that individual awareness and a responsibility one holds affect pro-environmental actions.

[2] TPB is formulated by Ajzen (1980), Understanding Events - Affect and the Construction of Social-Action - Heise,Dr. Contemp Psychol 25, 775–776, based on the Theory Reasoned Action. It is one of the most influential theories in social and health psychology Armitage and Conner, (2001), Efficacy of the theory of planned behavior: A meta-analytic review. Brit J Soc Psychol 40, 471–499, Onwezen et al. (2013), The Norm Activation Model: An exploration of the functions of anticipated pride and guilt in pro-environmental behavior. J Econ Psychol 39, 141–153. TPB assumes that an intention to act is determined by 3 main factors: human attitude toward specific behavior (action), subjective norm, and perceived behavioral control.

**Table 2**
Use of various decision-making theories to specify behavioral rules in environmental and energy ABM.

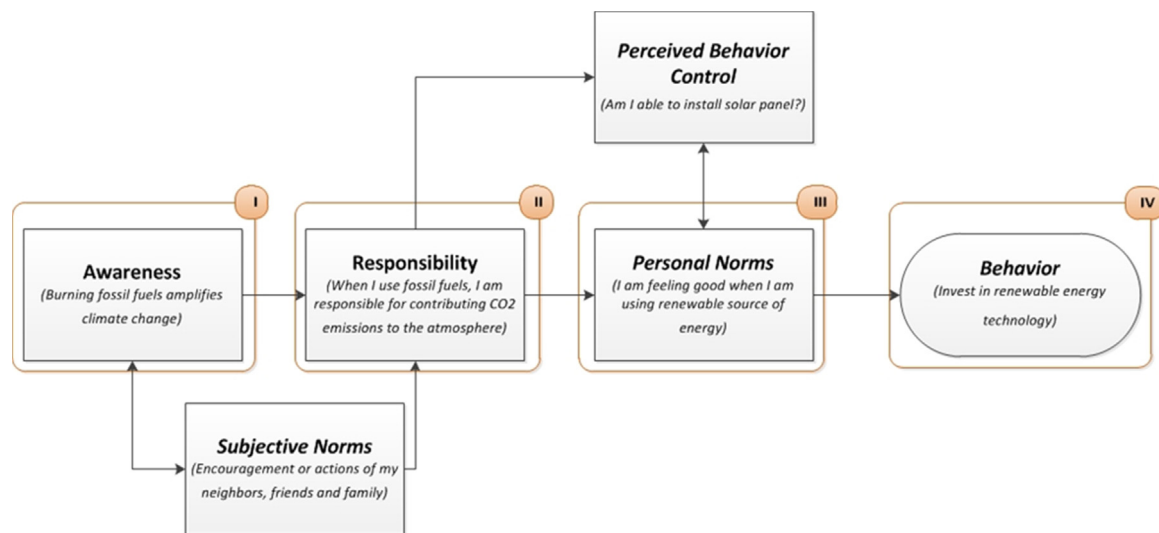| Theory / field | Energy | Other environmental (waste, agriculture, water) |
|---|---|---|
| Theory of planned behavior | Raihanian et al. (2017) | Ceschi Ceschi et al. (2015) |
| | Rai and Henry (2016) | Kiesling et al. (2012) |
| | Rai and Robinson (2015) | Schwarz and Ernst (2009) |
| Norm activation theory | Niamir and Filatova (2016) | – |
| Protection motivation theory | – | Haer et al. (2016) |
| | | Krömker et al. (2008) |
| Prospect theory | – | de Koning et al. (2017), Haer et al. (2016) |
| Goal-framing theory | Gotts and Polhill (2017) | Rangoni and Jager (2017) |
| | Polhill and Gotts (2017) | |
| Maximization, either with perfectly or boundedly rational agents | Cao et al. (2017) | Jager et al. (2000) |
| | Vasiljevska et al. (2017) | Filatova et al. (2011) |
| | Gallo (2016) | Parker et al. (2003) |
| | Gerst et al. (2013) | |
| | Weidlich and Veit (2008) | |
| Consumat approach | Bravo et al. (2013) | van Duinen et al. (2016) |
| | | Jager et al. (2000) |
| No theory framework | Palmer et al. (2015) | Groeneveld et al. (2017) |
| | Amouroux et al. (2013) | Kamara-Esteban et al. (2016) |
| | Chappin and Afman (2013) | Rounsevell et al. (2014) |
| | Chappin (2012) | Liu et al. (2006) |
| | Chappin and Dijkema (2007) | Gotts et al. (2003) |



**Fig. 1.** Conceptual representation of the Norm Activation Theory (Adapted from Schwartz (1977) and De Groot and Steg (2009)). A decision-making process leading to a particular behavior follows 5 main consecutive factors: awareness, responsibility, personal norms, subjective norms and perceived behavior control. In order to reach to a particular behavior (box IV), first an individual should be aware about an issue at hand (box I). A sufficient level of awareness then leads it to the feeling of responsibility (box II). Here the perceived social pressure – labelled as subjective norms in NAT (the linking box I-II) – could act as a mediating factor that raises or suppresses individual awareness and feelings of responsibility. Perceived behavior control (the linking box II- III) indicates an extent, to which performing a particular behavior could be easy or difficult for an individual. Finally, personal norms (box III) represents a moral obligation triggering the behavioral change.

income), socio-demographic (e.g. educational level, age), social (e.g. subjective and social norms), structural and physical (e.g. energy label and ownership of dwelling) drivers and barriers are considered and estimated based on the NAT theory (Fig. 1). Survey data indicates, which of these factors acts as a driver or as a barrier. Appendix A provides examples of questions used to measure each of the actions – investment, conservation and switching – and the relevant behavioral factors affecting these decisions.

Fig. 2 indicates the stages behind each decision, i.e. behavioral change, of a household. First, households should reach a certain level of *knowledge* and *awareness* about climate change, energy, and environment. If an individual in a household is aware enough, she might *feel guilt*. Here *personal norms* (individual attitudes and beliefs) and *subjective norms* prevailing in a society add to her *motivation*. If a household gets motivated, she feels *responsible* to do something. Still, none of them is enough to provoke an action or change behavior. A household should

*consider* her economic status, her house conditions (e.g. renting of owning), her current habits, and own perception of her ability to perform an action or change behavior, i.e. own PBC. If a household reaches a certain level of *intention*, we can expect that she is going to make a decision or act. This conceptual model is designed to investigate the multi-stage process of energy-related behavior change of households.

Tables 3–5 provide a brief overview of the survey sample to illustrate the distribution of the most important factors – including the key behavioral variables – across various income groups. The variation in these factors among surveyed households, as registered in the 2016 responses, is used to initialize[3] a population of heterogeneous agents in the ABM (Section 3.2).

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[3] The dynamics in the model is further driven by interactions among agents: market interactions, e.g. due to changes in aggregate demand and corresponding price dynamics, and social interactions, e.g. exchanging information about knowledge and awareness regarding energy and environment.
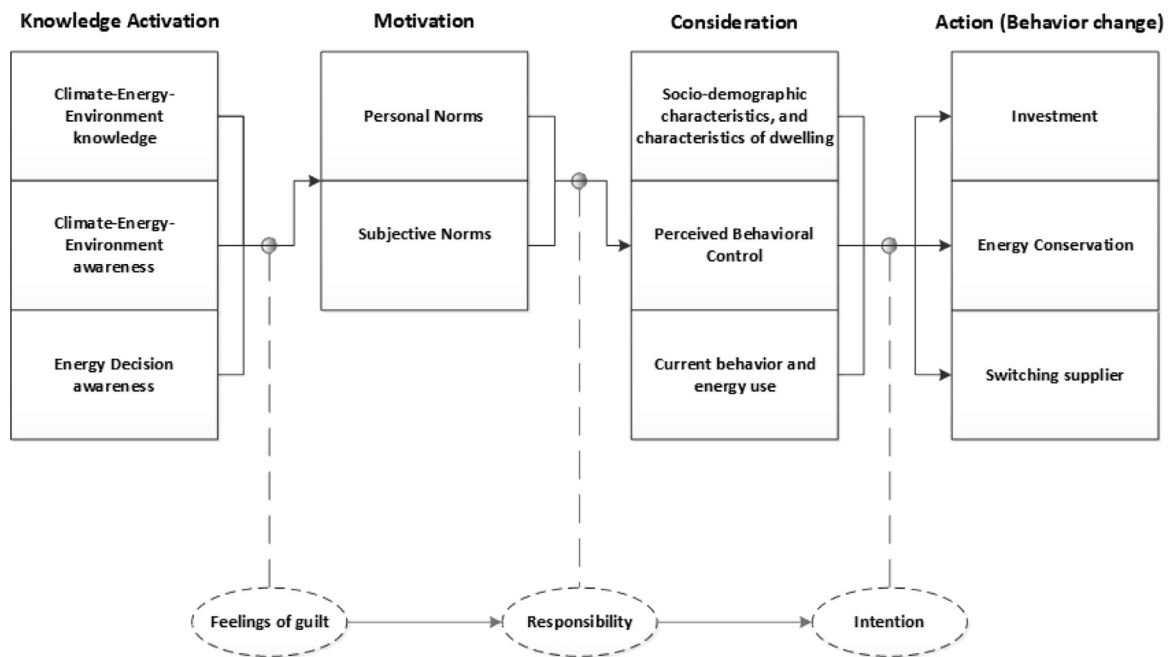
**Fig. 2.** Conceptual model underlying the household survey.

In addition to socio-demographic and energy use data (Table 3), we provide a summary of the distribution of behavioral factors (Table 4) and undertaken energy use choices (Table 5) reported by the households in our sample. The behavioral factors listed in Table 4 are measured by means of a questionnaire in our survey (please see examples of the questions used to elicit these behavioral factors in Appendix A). Data from Tables 3 and 4 is used to parameterize behavioral rules in the BENCH model as discussed further in Section 3.2.

Table 5 indicate that households in the Navarre region prefer an investment in energy efficient technology to either change in habits or switching to a greener electricity provider. Interestingly, this trend persists across all income groups. Conservation, which relates to changes in habits leading to a decrease in energy use, in general increases with income level. Pro-environmental behavior is more likely to occur in the middle-high rather than in lower income groups, while the top income group (7) falls out as an exception in this trend. It shows that households in the top income group are more interested in investment rather than conservation and switching, which economically makes sense. Switching receives the lowest share in comparison to the two other actions (investment and conservation). Yet, we observe some switching happening among the middle-low income households.

### 3.2. Agent-based model of residential energy choices

The *BENCH* model is designed to investigate a process of individual (household) energy-related decision-making, and to study the cumulative impacts of behavioral changes among heterogeneous households over time and space. *BENCH* primarily focuses on the residential demand side with a possibility to represent feedbacks between the energy supply and the residential demand in a retail energy market. The decision-making of energy producers on the supply side is modeled simplistically as profit maximization, given the available set of technologies that come as exogenous scenarios at initialization (Niamir and Filatova, 2015). The supply side is modeled explicitly within the model to enable market dynamics, in particular the market clearing procedure, and to trace feedbacks between individual household behavioral changes and cumulative impacts of excess of grey/green energy demand or supply through adapting prices. Thus, in the current model there are two representative electricity provider agents (grey and

green) and 3468 household agents, which are geographically spread over the territory of a province in Spain (Navarre) in this application. We create the synthetic population of households in BENCH by drawing the households' economic and behavioral characteristics from the survey data, using either averages or the exact empirical distributions depending on the simulation experiment (Table 6). To expand our 800 sample to a larger population, we use the actual proportion of population in the Navarre region in each income group to scale up; this data comes from the Eurostat Households Budget dataset (2010). After identifying how many households should belong to which income class, we draw other economic, energy use and behavioral characteristics from the survey data summarized per income class in Tables 3–5. The model is coded in NetLogo 5.2 with GIS extension (Wilensky, 1999). We used open source applications, such as PostgreSQL and R, for the spatio-temporal and statistical analyses (Fig. 3).
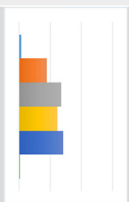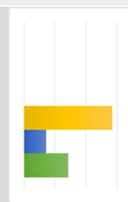
#### 3.2.1. Demand side

The demand side in *BENCH* consists of heterogeneous households with different socio-economic characteristics, preferences, and awareness of environment and climate change, which lead them to various energy consumption choices and actions. As it is illustrated in Fig. 4, based on different internal and external barriers and drivers, households have different knowledge and awareness levels about the state of the climate and environmental issues (Box I), motivation levels to change their energy related behavior (Box II), and consideration levels (Box III) when they perform costs and utility assessments. This decision process closely follows the conceptual NAT-based framework (Fig. 1) behind the household survey (Fig. 2) and applies to all the three groups of energy-related actions (Table 1). All household attributes could potentially be heterogeneous and change over time and space. All the variables in knowledge activation, motivation and consideration are measured in comparable ways with the Likert scale, ranging from 1(low) to 7 (high) in the survey.

At initialization, household *knowledge and awareness* (K) is assigned a value based on the survey data. We estimate an average of climate-energy-environment knowledge (CEEK), awareness (CEEA), and energy-related decision awareness (EDA) values, each measured on a 7 score Likert scale.

**Table 3**
Descriptive statistics of the survey sample on socio-demographic and structural characteristics, Spain-Navarre.
*Source*: Own survey, 2016.

| Income groups, Thousands euro per year | < 10 | 10 - 30 | 30 - 50 | 50 - 70 | 70 - 90 | 90 - 110 | >110 |
|---|---|---|---|---|---|---|---|
| **Socio-demographic factors** | | | | | | | |
| **Share of population,** % from the total | 11.39% | 46.75% | 27.81% | 8.74% | 3.05% | 0.93% | 1.32% |
| **Level of education,**<br>■ Primary<br>■ Secondary<br>■ Tertiary<br>■ BSc<br>■ MSc<br>■ Doctoral |  |  |  |  |  |  |  |
| **LCE user,** % in each income group | 3.49% | 4.25% | 5.71% | 3.03% | 13.4% | 0 | 0 |
| **Annual electricity use,** in kWh | 1932.6 | 1564.9 | 2036.2 | 2303.6 | 2394.9 | 1143 | 2261.9 |
| **Structural and Physical (Housing) factors** | | | | | | | |
| **House energy label,**<br>■ A<br>■ B<br>■ C<br>■ D<br>■ E<br>■ F |  |  |  |  |  |  |  |
| **House owner, %** in each income group | 37% | 78% | 85% | 94% | 96% | 86% | 80% |

$$K = \frac{\text{Average } (CEEK, CEEA, EDA)}{7} \quad (1)$$

Further, on each time step household agents calculate their current individual level of *knowledge and awareness* (Low or High) based on the $K$ value (Eq. (1)). If households are aware enough, that is they have a high level of knowledge and awareness above the threshold of 4 out of 7, then they are tagged as "feeling guilt" and proceed to the next step to assess their *motivation*.

Household personal norms (PN) and subjective norms (SN) are checked to calculate their *motivation* (M, Eq. (2)).

$$M = \frac{\text{Average } (PN, SN)}{7} \quad (2)$$

*Motivation* may differ for each of the three main actions. For example, a household may have a high level of motivation for installing solar panels, and is tagged with "responsibility" for Action1

**Table 4**
Descriptive statistics of the survey sample on psychological factors, Spain-Navarre.
*Source*: Own survey, 2016.

| Income groups, Thousands euro per year | < 10 | 10 − 30 | 30 − 50 | 50 − 70 | 70 − 90 | 90 − 110 | > 110 |
|---|---|---|---|---|---|---|---|
| **Psychological factors** | | | | | | | |
| **Awareness**, average on the scale 0 (not aware) − 7 (very aware) | 5.23 | 5.20 | 5.13 | 5.24 | 5.45 | 5.15 | 5.30 |
| **Personal norms**, average on the scale 0 (weak) − 7 (strong) | 5.35 | 5.40 | 5.36 | 5.43 | 5.47 | 5.16 | 5.46 |
| **Subjective norms**, average on the scale 0 (weak) − 7 (strong) | 4.38 | 4.46 | 4.46 | 4.32 | 4.54 | 4.32 | 4.69 |
| **Energy-efficient habits and patterns**, average on the scale 1 (always) - 3 (seldom) | 1.20 | 1.17 | 1.20 | 1.17 | 1.19 | 1.19 | 1.44 |
| **PBC1**, average on the scale 0 (weak) − 7 (strong) | 4.92 | 5.06 | 5.21 | 5.04 | 5.05 | 4.31 | 5.60 |
| **PBC2**, average on the scale 0 (weak) − 7 (strong) | 4.66 | 4.88 | 4.91 | 4.70 | 4.83 | 4.07 | 4.75 |
| **PBC3**, average on the scale 0 (weak) − 7 (strong) | 5.08 | 5.23 | 5.18 | 5.11 | 4.96 | 4.57 | 5.00 |

**Table 5**
Descriptive statistics of the survey sample on already undertaken energy-related actions, Spain-Navarre.
*Source*: Own survey, 2016.

| Income groups, Thousands euro per year | < 10 | 10 − 30 | 30 − 50 | 50 − 70 | 70 − 90 | 90 − 110 | > 110 |
|---|---|---|---|---|---|---|---|
| **Share of households who have undertaken energy-related actions** | | | | | | | |
| **Action 1 (investment)**, % in each income group | 59.3 | 63.1 | 55.7 | 48.4 | 52.1 | 71.4 | 60 |
| **Action 2 (conservation)**, % in each income group | 4.6 | 3.3 | 5.2 | 7.5 | 8.6 | 14.2 | 0 |
| **Action 3 (switching)**, % in each income group | 0 | 0.56 | 0.95 | 1.51 | 0 | 0 | 0 |

(investment) and proceeds to the next step (*consideration*). At the same time, it may not pass the threshold value (4) in *motivation* for changing energy use habits or switching to another energy supplier (Actions 2 and 3), and thus does not go into the *consideration* step on those two actions.

Thirdly, if household agents have a high motivation level and feel responsibility, they consider the psychological (e.g. PBC), structural (housing attributes) and institutional factors to assess utility and costs of a specific action. Then, households with high level of *consideration* are tagged as "high intention". Their *intention* (*C*, Eq. (3)) is measured based on consideration factors.

$$C = \frac{PBC}{7} \tag{3}$$

In the *consideration* stage, as well as the *motivation* stage, we differentiate between actions. In investment for instance, the dwelling ownership status (owner or rental dwelling), the energy label of the dwelling, and perceived behavioral control over the perceived affordability of an investment are assessed. For the initialization of *BENCH*, all these main variables, awareness (K), motivation (M), and intention (C), are calculated based on the survey data (Section 3.1 and Appendix A).

Fourthly, if a household agent has high intentions to undertake any of the three main actions for making an energy decision, we calculate its expectations about utility (U) based on its current energy source status (green or grey energy user). Energy economics (Bhattacharyya, 2011) assumes that households receive utility (Eq. (4)) from consuming energy (E) and a composite good[4] (Z) under budget constrains (Eq. (6)):

$$U = \alpha. Z + \beta. E$$
$$E = Q. P \tag{4}$$

Here α is a share of an individual annual income spent on the composite good and β is a share spent on energy, with α + β = 1; Q is the amount of electricity consumption in Kwh and P is price of electricity. We further extend it by including the influence of knowledge and awareness (K), motivation (M) and consideration (C) estimated using Eqs. (1)–(3):

$$U = \alpha. Z + \beta. E + K + M + C \tag{5}$$

On each time step t, Z is calculated based on the household total budget (Y), energy consumption (E), and economic costs or benefits involved in action 1 (I), 2 ($\theta^e$), and 3 ($\theta^p$):

$$Z_t = Y_t - (E_{t-1} + I_t + \theta_t^e + \theta_t^p) \tag{6}$$

Hence, both behavioral and economic factors affect households' decisions. To summarize, the household agents consider economic constrains in two stages. Firstly, whether pursuing an action (e.g. investment, switching or conservation) is affordable comes under individual perceived behavioral control assessment initialized from the survey data. Secondly, each individual utility is constrained by a household's budget (Eqs. 4–6), which is shared between energy consumption and a composite good. The behavioral factors (Eq. (5)) just extend the traditional economically-constrained utility (Eq. (4).). Any economic costs associated with pursuing an action – investment, conservation or switching – affect households' available budget (Eq. (6)).

Finally, to make their energy decisions, households first analyze their utility expectations (among three actions) to find the highest one and then compare it with their current utility. For instance, a household is going to perform an investment action if the following condition holds:

$$U_t^1 > Max\{U_t^2, U_t^3\} AND U_t^1 > U_{t-1}^1 \tag{7}$$

All the three actions that constitute behavioral change regarding residential energy use among households - investment, energy conservation, and switching to green provider - are assessed using this four-step procedure.

### 3.2.2. Supply side

The supply side is presented by two energy providers, which deliver electricity from either low carbon energy (LCE) or fossil fuel based (FF) sources. Initial shares of electricity production and energy production costs for the two energy producers come from macroeconomic data derived from the EXIOMOD CGE model[5] under the business as usual (SSP2) scenario. We acknowledge that this simplified assumption does not account for difference between day/night tariffs, fixed tariff schemes, technology diffusion, innovation and learning on the supply

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[4] A composite good is a typical assumption in microeconomics (Varian (1992), Microeconomic analysis, 3rd ed. Norton, New York.) to represent all other goods besides the one under study. In our case, it can be expressed as a part of a household budget to be spend on anything but energy, e.g. food, transport, housing.

[5] The EXIOMOD CGE model is designed at TNO in the Netherlands. https://repository.tudelft.nl/view/tno/uuid:3c658012–966 f-4e7a-8cfe-d92f258e109b/.
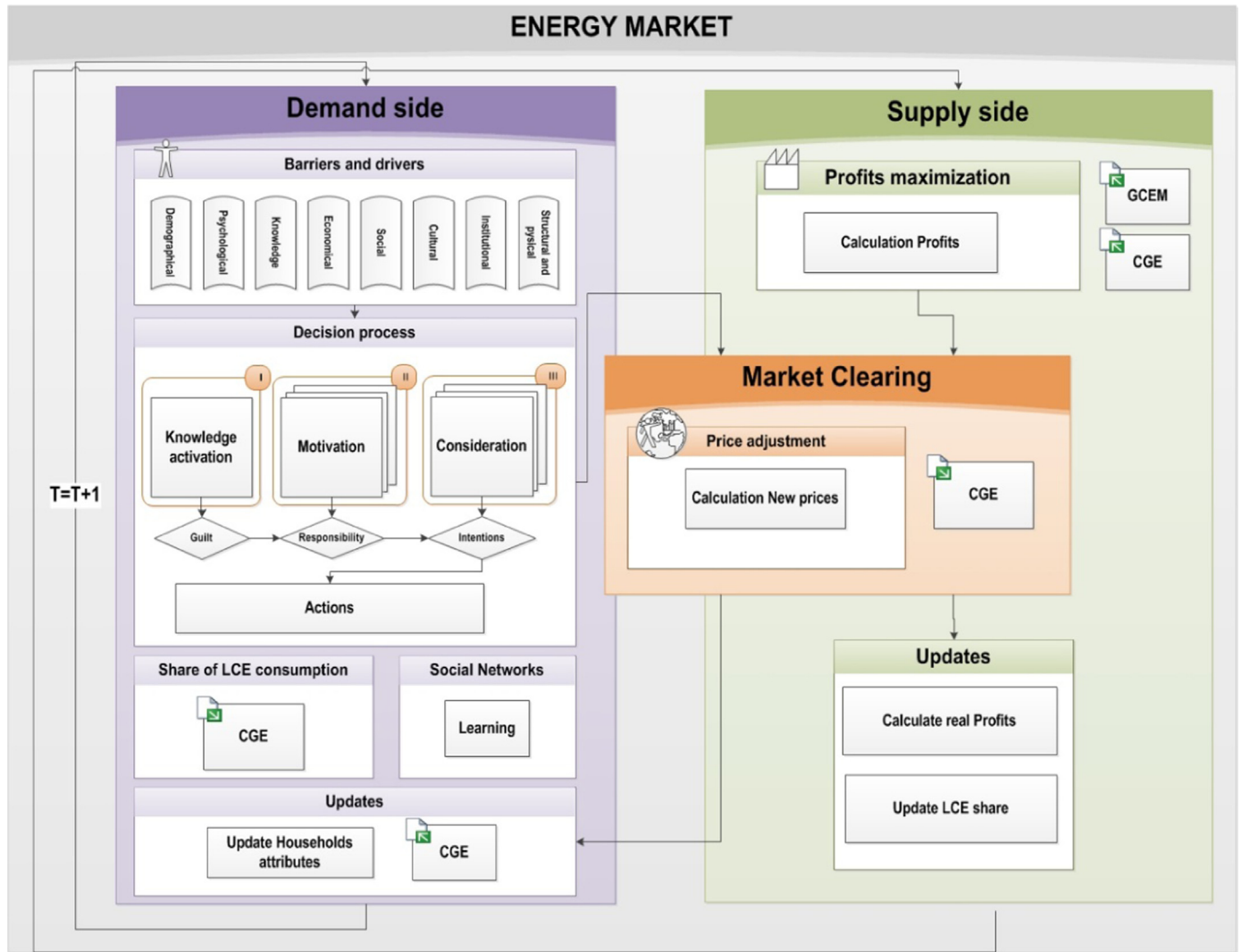
**Fig. 3.** Representation of the dynamics flows within the BENCH model.

side. Ideally, one could integrate the *BENCH* model with a more advanced energy supply model (Kowalska-Pyzalska et al., 2014; Salies, 2012). Yet, given the focus of this article, we leave this for future work. The current simplified supply side modeling implies that (i) only aggregated annual demand and supply are compared excluding a possibility to study behavior in peak energy use hours, (ii) scenarios with various tariff schemes and regulations on the supply side of the energy market have limited application here potentially leading to quicker energy price adjustments, (iii) technological innovation and learning do not yet affect costs of energy production. These are important directions in which this model can be extended or where it can link to others in energy supply simulations. Energy providers are modeled as profit seeking agents. In this simplified retail electricity market, expected profits are calculated based on expected prices ($P_{lce}$, $P_{ff}$), and shares of LCE and FF based energy planned for the next time step to maximize profits. Expected profit is calculated based on total expected revenue (R) and total production cost (C):

$$P = R - C \tag{8}$$

We consider cumulative price growth (CPG), market price of electricity (P), and electricity production (Q) to estimate the total revenue for an electricity producer (Eq. (9)). The CPG and Q come exogenously from the EXIOMOD macrodata, while P is endogenously defined on an annual basis (Section 3.2.3):

$$R = \text{CPG. P. Q} \tag{9}$$

### 3.2.3. Market clearing

Based on the review of ABM markets (Niamir and Filatova, 2015; Tesfatsion, 2006), Niamir and Filatova (2017) discuss five alternative market clearing procedures. In addition to the neoclassical Walrasian auctioneer, simulated markets often use a random matching, an order book, a bilateral trade or a gradual price adjustment. We choose the latter approach to model price expectation formation as it seems to represent the retail electricity market more accurately (Federico and Vives, 2008; Niamir and Filatova, 2015). Following LeBaron (2006), we assume that each time step the price ($P_t^e$) for each type of electricity ($e$ = [LCE;FF]) is anchored to the price in the previous year ($P_{t-1}^e$, Eq. 10).It further gradually adjusts depending on the excess of supply $S^e(P_{t-1}^e)$ or demand $D^e$ ($P_{t-1}^e$) in the previous time step. For example, if there was more grey electricity produced than demanded in *t-1*, then price for FF in period *t* will decrease, creating a disincentive for electricity suppliers to opt for FF. It is assumed that this adjustment occurs gradually, meaning that prices change only to a proportion (μ) of the demand/supply excess.

$$P_t^e = P_{t-1}^e + \mu(D^e(P_{t-1}^e) - S^e(P_{t-1}^e)) \tag{10}$$

Each time step *t* households and electricity provider agents make their decisions based on these price expectations ($P_t^e$), which are

**Table 6**
Experiments setting.

| Factors | Var | Exp1 | Exp2 | Exp3 | Exp4 | Exp5 | Exp6 |
|---|---|---|---|---|---|---|---|
| | | Economic factors: homo; Behavioral factors: no; Learning: no | Economic factors: hetero; Behavioral factors: no; Learning: no | Economic factors: hetero; Behavioral factors: homo; Learning: no | Economic factors: hetero; Behavioral factors: hetero; Learning: no | Economic factors: hetero; Behavioral factors: hetero; Learning: 1 | Economic factors: hetero; Behavioral factors: hetero; Learning: 2 |
| **Households attributes** | Y | 31426.91 (average, survey) | (0–150000) (survey distribution) | (0–150000) (survey distribution) | (0–150000) (survey distribution) | (0–150000) (survey distribution) | (0–150000) (survey distribution) |
| | C | 2777 (average, survey) | (1000–150000) (survey distribution) | (1000–150000) (survey distribution) | (1000–150000) (survey distribution) | (1000–150000) (survey distribution) | (1000–150000) (survey distribution) |
| | HS | Grey (majority, survey) | (green, grey) (survey distribution) | (green, grey) (survey distribution) | (green, grey) (survey distribution) | (green, grey) (survey distribution) | (green, grey) (survey distribution) |
| | DT | owner (majority, survey) | (owner, rental) (survey distribution) | (owner, rental) (survey distribution) | (owner, rental) (survey distribution) | (owner, rental) (survey distribution) | (owner, rental) (survey distribution) |
| | DEL | B (majority, survey) | (A,B,C,D,E,F) (survey distribution) | (A,B,C,D,E,F) (survey distribution) | (A,B,C,D,E,F) (survey distribution) | (A,B,C,D,E,F) (survey distribution) | (A,B,C,D,E,F) (survey distribution) |
| | HEP | 1.20 (average, survey) | (1.00–3.00) (survey distribution) | (1.00–3.00) (survey distribution) | (1.00–3.00) (survey distribution) | (1.00–3.00) (survey distribution) | (1.00–3.00) (survey distribution) |
| **Psychological factors** | CEEK | – | – | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) |
| | CEEA | – | – | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) |
| | EDA | – | – | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) |
| | PN | – | – | 5.37 (average, survey) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) |
| | SN | – | – | 4.45 (average, survey) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) |
| | PBC1 | 5.03 (average, survey) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) |
| | PBC2 | 4.68 (average, survey) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) |
| | PBC3 | 5.02 (average, survey) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) | (1–7) (survey distribution) |
| **Learning and Social network** | | – | – | – | – | Learning in Knowledge activation (CEEK, CEEA, EDA) | Learning in Knowledge activation and Motivation (CEEK, CEEA, EDA, PN, SN) |

updated after the aggregate market demand ($D_t^e$) and supply ($S_t^e$) are known in the next period $t + 1$. Thus, households form expectations about their utility (U, Eqs. 4–6) based on the expected price ($P_t^e$, Eq. (10)) and follow a satisfying behavior by choosing a better option among the available ones (Eq. (7)) giving this limited information. Moreover, the households agents change their energy use decisions following a cognitive process (see 3.2.1) inspired by psychological theories (Niamir and Filatova, 2016). Hence, there is always a possibility of a behavioral change at the individual level driven by updates in expectations, prices and behavioral factors. It implies that this ABM market does not settle in a unique equilibrium, as would be the case in markets with rational optimizers and perfect information.

In this approach households are satisfied by choosing an action that gives them higher – but not necessary maximal – utility through forming expectations about utility of an action vs. status quo (inaction) based on the previous period prices for LCE and FF energy. The new energy prices for both types of energy ($P_t^e$) and market shares of LCE and FF electricity are emergent outcomes of changes in individual energy demand of many interacting heterogeneous household agents in our model. At the last stage, utilities of households and profits of providers are updated based on new prices ($P_t^e$).

### 3.3. Experiments setup

In line with the research question, we design several model experiments (Table 6). Namely, we explore: (1) the impact of heterogeneity in household attributes such as income and electricity consumption (comparison of Exp1 and Exp2); (2) the additive effect of psychological factors, such as personal norms and social norms (comparison of Exp3 and Exp4); and (3) the influence of interactions through social networks and learning (information diffusion), on the energy-related decisions (comparison of Exp5 and Exp6). In all cases, we study behavioral changes among households differentiating between 3 actions: energy investment, conservation and switching. For each we assess the following macro-metrics: the diffusion of each of the three types of behavioral actions among households over time, and the changes in saved energy and $CO_2$ emissions.
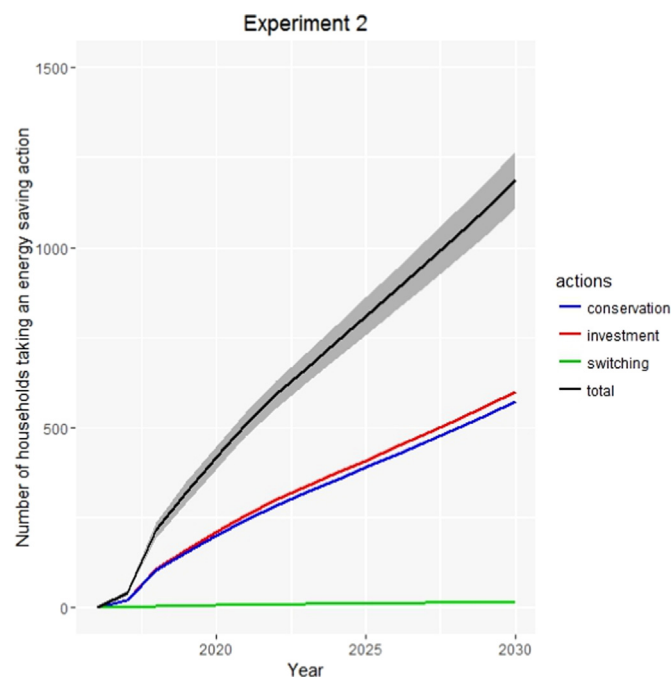


**Fig. 4.** Diffusion of energy-related actions among household heterogeneous economic and housing attributes (Exp2). The grey bounds around the curves indicate the uncertainty intervals across 100 Monte Carlo runs.

Impact of heterogeneity in household economic attributes (Exp1, Exp2): the household agents in the BENCH model are differentiated by a number of economic and physical factors. Namely: annual income in euro (Y); annual electricity consumption in Kwh (C); household status in terms of being a green or grey electricity user (HS); dwelling tenure status showing whether a household is an owner or a renter (DT); energy label of a dwelling (DEL) varying from A to F; and the household energy use routines and habits (HEP) (Appendix A). Most of these data is directly observable and registered in traditional datasets such as census or Eurostat microdata. Yet, the information is often aggregated to a national, regional or income group level. To test the impact of using average values for each attribute (see Y, C, HS, DT, DEL and HEP, Table 6) vs. their empirical distribution we initialize the synthetic population in BENCH with the values either equal to the average of our survey (Exp1) or their empirical distribution (Exp2). Hence, in Exp1 household agents are all alike. In Exp2 individual agents differ on the attributes Y, C, HS, DT, DEL and HEP. Yet, the average values of these attributes in Exp2 are equal to the homogeneous value of these parameters in Exp1, making the two populations on average the same.

Impact of behavioral attributes and behavioral heterogeneity (Exp3, Exp4): Individual decisions, including energy use choices, could be influenced by behavioral barriers and stimuli. In addition to the rational decision maker model of an individual household (Exp1 and 2), we explore cumulative regional level impacts of behavioral factors affecting individual agents' choices (Exp3 and 4). The psychological aspects impacting households' energy related decisions include individual knowledge and awareness (CEEK, CEEA and EDA), motivation (PN, SN), and perceived behavioral control over the 3 types of actions (PBC1-PBC3). Appendix A clarifies the definitions and survey measures used to quantify these attributes and Tables 3–5 provide summary statistics of the corresponding survey responses. We run two experiments to test the impact of heterogeneity in the behavioral factors, which are rarely directly observable and are often omitted when modeling energy demand. In Exp3 we initialize the population of agents using the survey data on household behavioral attributes (CEEK, CEEA, EDA, PN, SN, Table 6) with the consideration of the heterogeneity in knowledge and awareness (CEE, CEEA, EDA). For the population of households in Exp4 the values of these attributes are drawn from their corresponding empirical distributions from our survey. As before, the average values of behavioral attributes in the heterogeneous population in Exp4 are equal to the homogeneous value of these parameters in Exp3, making the two populations *on average* the same.

Impact of social network interactions and learning (Exp5, Exp6): agent-based simulations offer an opportunity to go beyond static behavior and explore the impacts of learning and information exchange via social networks, which are argued to be important in the diffusion of energy-efficient practices among households (Rai and Robinson, 2015). We extend the previous experiments by directly modeling information exchange among households regarding their knowledge (CEEK, CEEA and EDA, Exp5 in Table 6). We assume that households engage in social interactions with maximum 8 neighbors surrounding their current location. While knowledge may be passive, we test the impact of learning by assuming that household agents also can exchange opinions about their motivation (PN and SN, Exp6 in Table 6). We employ an opinion dynamics model (Acemoglu and Ozdaglar, 2011; Degroot, 1974; Hegselmann and Krause, 2002; Moussaid et al., 2015) in which agents compare values of their own behavioral factors – awareness and motivation – with those of their 8 closest neighbors, and adjust their value to become the mean of the 9 compared values. Therefore, Exp5 and 6 study the regional level impacts of the micro-level diffusion of information on awareness and motivation of heterogeneous households transmitted through social networks.

### 4. Results and discussion

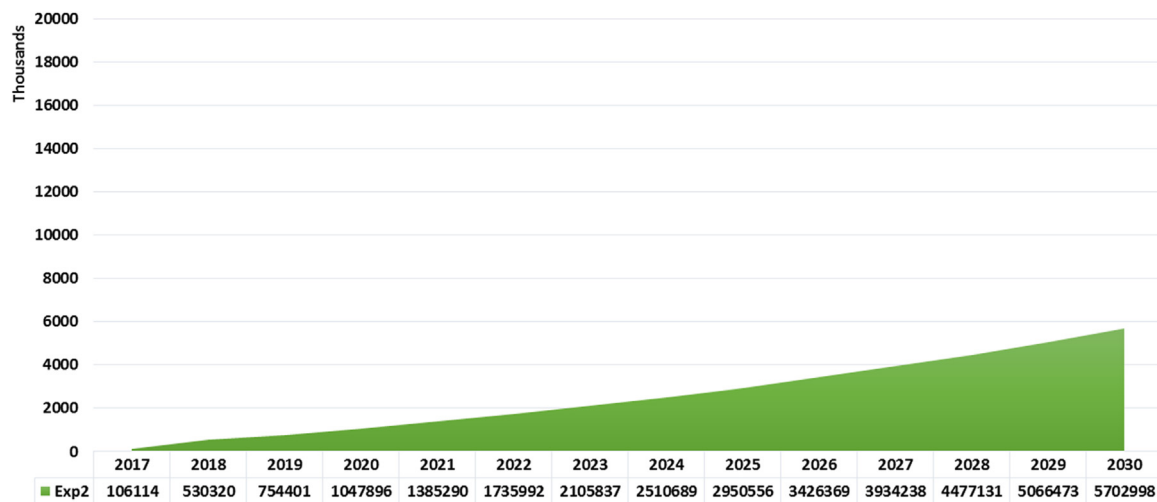In what follows, we present the results of the *BENCH* model by

Fig. 5. Cumulative saved energy (kWh) by heterogeneous (in economic and physical and housing attributes) households' energy-related actions (Exp2).

**Table 7**

Distribution of the climate mitigation efforts among various socio-economic groups and dwelling types, assuming households are heterogeneous in economic and physical attributes (Exp2). MWh (percent (%), contribution of each individual group in total saved energy).

| Socio-economic groups | | Cumulative saved electricity, in MWh | |
|---|---|---|---|
| | | 2020 | 2030 |
| Income groups (thousands euro per year) | 1 (< 10) | 229 (15%) | 1371 (16%) |
| | *2 (10–30)* | *811 (53%)* | *4756 (56%)* |
| | 3 (30–50) | 348 (23%) | 1818 (21%) |
| | 4 (50–70) | 103 (7%) | 426 (5%) |
| | 5 (70–90) | 17 (1%) | 58 (1%) |
| | *6 (90–110)* | *0 (0%)* | *0 (0%)* |
| | 7 (> 110) | 10 (1%) | 44 (1%) |
| Dwelling energy label | A | 461 (30%) | 2572 (30%) |
| | *B* | *444 (29%)* | *2390 (28%)* |
| | C | 290 (19%) | 1610 (19%) |
| | D | 166 (11%) | 968 (11%) |
| | E | 85 (6%) | 7550 (6%) |
| | *F* | *73 (5%)* | *382 (5%)* |

tracking individual and cumulative impacts of behavioral changes among 3468 individual households in the Navarre region in Spain over 14 years (2016–2030). Given the stochastic nature of ABMs, we perform multiple (N = 100) repetitive runs of each simulation experiment (Lee et al., 2015). All the results presented below report the mean values across 100 runs to assure that resulting values are not an artifact of a random seed number but a stable trend considering the assumptions of each experiment.

*4.1. The role of economic heterogeneity: income and housing factors*

In Exp1 all household agents have the same income, electricity consumption, and dwelling conditions. They are assumed to be rational as they encounter no behavioral biases such as those that could be driven by psychological (personal norms and attitudes) or social factors (influence of social network). To assure that the benchmark is comparable to the population with heterogeneous agents, for this experiment we parameterize agents with the averages of the survey data. Given our survey parameterization, it appears inefficient for this population of representative agents in Exp1 to take any action. Namely, the household agents in the model would pursue any of the energy-related actions – investment, conservation, or switching – only when those improve their status quo. In Exp1, the representative agent

parameterized with the means of the survey data compares its current utility of business as usual with taking one of the 3 actions. However, the latter appears to be lower for this stylized homogeneous population of households. Exp1 results hardly relate to reality, in which households are heterogeneous in incomes, dwellings types, energy use habits and behavioral factors affecting individual energy choices. Exp1 is designed to set a baseline of an energy market with homogenous and rational households, resembling a representative rational agent set up common in aggregated models.

In Exp 2 we add the heterogeneity to the agents' economic and housing attributes. Here we have households with various incomes, electricity consumption, and dwelling conditions parameterized using our survey data. Note that in both the baseline experiment and in Exp 2 knowledge activation, motivation, and the learning process are not activated (Table 6). Thus, agents from different income groups residing in houses of different quality are still homogenous in terms of their behavior decision process. Fig. 4 shows that introducing the heterogeneity to the household economic and housing attributes produces a significant increase in the diffusion of energy-related actions, and that this trend is nonlinear. We observe that the diffusion of actions continues for 14 years (2016–2030) on average across 100 simulation runs. Interestingly, the simulation trends show that households are more eager to invest, for example in solar panels and insulation, and to change energy-use habits (600 and 572 households respectively) rather than to switch to a green supplier (17 households, accounting just for 0.5% of the entire population). Our survey data also reveals that currently the majority of respondents in the Navarre region prefer to invest rather than follow the other two actions (Table 5). There could be different reasons behind this outcome, ranging from the past economic policies, e.g. taxes and subsidies, to a lack of knowledge and motivation for other two actions (energy conservation and switching). Our survey indicates that there is a lack of information on how household could save energy and lack of motivation to change a supplier. In general, electricity prices in Spain are high compared to the European average and there is less choice in terms of suppliers and renewable energy sources (Ciarreta et al., 2014, 2017). This may partially explain why households do not see much benefits in switching to an alternative energy source. The interest in investments could be also an echo of the past. There were many governmental subsidies for installing solar panels in early 2000s (del Río and Unruh, 2007), fueling the flow of information and motivations toward this particular energy-efficient action. This might change over time based on changes in policies and households' awareness.

Fig. 5 presents the amount of the saved energy (kWh) due to the households' energy-related actions reaching up to 6000 kWh by 2030.

**Fig. 6.** Diffusion of energy-related actions among households when agents, which are heterogeneous in economic and housing factors, replace a one shot decision process by a cognitive one relaying on psychological factors. (a) Propagation of the 3 types of behavioral changes in a population of agents with diverse awareness and knowledge activation but homogeneous motivation. (Exp3); (b) Propagation of the 3 types of behavioral changes in a population of agents with diverse awareness as well as diverse motivation (Exp4).
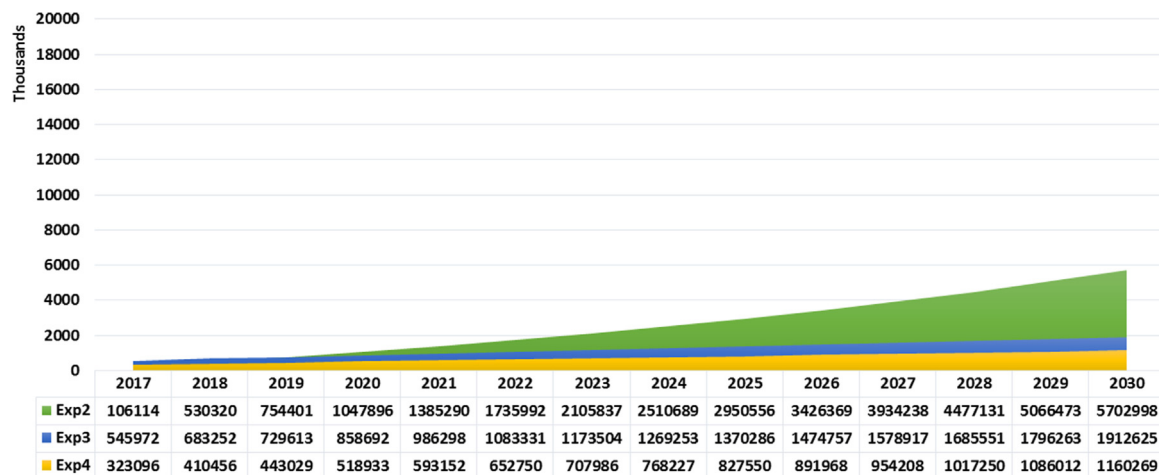


| | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ■ Exp2 | 106114 | 530320 | 754401 | 1047896 | 1385290 | 1735992 | 2105837 | 2510689 | 2950556 | 3426369 | 3934238 | 4477131 | 5066473 | 5702998 |
| ■ Exp3 | 545972 | 683252 | 729613 | 858692 | 986298 | 1083331 | 1173504 | 1269253 | 1370286 | 1474757 | 1578917 | 1685551 | 1796263 | 1912625 |
| ■ Exp4 | 323096 | 410456 | 443029 | 518933 | 593152 | 652750 | 707986 | 768227 | 827550 | 891968 | 954208 | 1017250 | 1086012 | 1160269 |

**Fig. 7.** Saved energy in kWh (Experiment 3, 4 and Experiment 2 as a benchmark).

The saved electricity (kWh) is unequally distributed among various income groups and various types of energy-efficiency of buildings (Table 7). In this table the contribution percentage (%) of each individual group in the total saved energy is reported in the parenthesis. As a matter of fact, the two richest household groups – from 90 to 110 + thousand euro per year – are behind in this energy saving process. It may have to do with the fact that a rich household lifestyle creates a norm for an energy-intensive behavior. The pioneers are, however, the first 3 bottom income groups: contributing 91% and 93% cumulatively in 2020 and 2030. The households in the second income group (10–30 thousand euro per year) contribute more than 50% to this energy-related effort. There is also a slight change in the distribution of this effort across the income groups over time between 2020 and 2030 but the general trend remains. The distribution across dwellings with different energy labels is less extreme: the households residing in buildings with

A and B energy labels save each about 30% of energy gained within this region through their behavioral change actions.

In fact, Exp1 and 2 present an outcome that is to be expected if we assume that households make energy-related decisions in a rational manner. In other words, if a household foresees any gain in utility by undertaking an action, the behavior change occurs immediately. In practice the latter is a process involving several stages and factors that potentially all serve as barriers to the individually-optimal state and the efficient level of diffusion of positive energy-use practices at the societal level (Cleveland and Ayres, 2004; Malama et al., 2015). This optimistic view on human rationality may be the reason behind the overestimation of diffusion of PVs, or insulation practices and green electricity by models grounded in the rational optimizer agent. In order to be able to take a wider view and integrate empirical social science knowledge on barriers and triggers along an individual path towards a

**Table 8**

Distribution of the climate mitigation efforts among various socio-economic groups and dwelling types, assuming households are affected by psychological factors and may exhibit behavioral heterogeneity (Exp3 and Exp4). MWh (percent (%), contribution of each individual group in total saved energy).

| Socio-economic groups | | Cumulative saved electricity, in MWh | | | |
|---|---|---|---|---|---|
| | | 2020 | | 2030 | |
| Experiments | | Exp3 | Exp4 | Exp3 | Exp4 |
| Income groups (in thousands euro per year) | 1 (< 10) | 173 (11%) | 79 (10%) | 471 (12%) | 325 (15%) |
| | *2 (10–30)* | *468 (31%)* | *235 (28%)* | *1546 (40%)* | *843 (40%)* |
| | 3 (30–50) | 234 (16%) | 170 (21%) | 855 (22%) | 454 (21%) |
| | 4 (50–70) | 401 (27%) | 194 (23%) | 645 (17%) | 283 (13%) |
| | 5 (70–90) | 202 (13%) | 118 (14%) | 291 (8%) | 176 (8%) |
| | *6 (90–110)* | 24 (2%) | *20 (2%)* | 27 (1%) | *27 (1%)* |
| | *7 (> 110)* | *7 (0%)* | 10 (1%) | *10 (0%)* | 17 (1%) |
| Dwelling energy label | A | 230 (15%) | 169 (20.4%) | 764 (20%) | 458.1 (23.6%) |
| | *B* | *508 (34%)* | *235.6 (28.5%)* | *1269 (33%)* | *672.1 (34.7%)* |
| | C | 438 (29%) | 224.4 (27.1%) | 960 (25%) | 424.1 (21.9%) |
| | D | 164 (11%) | 105.4 (12.7%) | 436 (11%) | 218.9 (11.3%) |
| | E | 114 (8%) | 71.4 (8.6%) | 290 (8%) | 122.4 (6.32%) |
| | *F* | *54 (4%)* | *20.4 (2.4%)* | *126 (3%)* | *40.8 (2.1%)* |
| Total (compared to the Exp2 in percent) | | 1509 (99%) | 826 (54%) | 3845(45%) | 2125 (25%) |

specific action (Fig. 2), we run the next set of experiments with our ABM.

### 4.2. The role of behavioral heterogeneity: psychological factors

To quantify individual psychological drivers in household energy-related decisions and the cumulative impacts of these decisions, we compare Exp3 and 4. Both experiments extend Exp2 by adding the knowledge activation and motivation stages in household decision process (Section 3.1), thus modeling the cognitive process of decision making rather than assuming that it is a one-shot choice. In both experiments, the knowledge activation elements – CEE knowledge, CEE awareness and ED awareness – are heterogeneous and initialized based on the empirical distribution from the survey (Table 6, Appendix A). Factors relevant at the motivation stage – personal and subjective norms – are considered homogenous and are set to the average of the survey data in Exp3. In Exp4 they are heterogeneous following our survey distributions (Table 6). The outcomes of Exp3 indicate what happens if we explicitly assume that decision-making is a process influenced by behavioral factors such as awareness and motivation. Thus, the *BENCH* model encompasses two additional stages before any actual action takes place. We present the runs of Exp3 with households endowed with heterogeneous awareness and homogeneous motivation to trace their effects separately.[6] Exp4 demonstrates a scenario when individual households process these steps in a heterogeneous manner. Neither Exp3 nor 4 considers any learning processes (Table 6).

Exp1 and 2 assume a rational optimizer agent that undertakes an energy-related choice immediately if utility of an action exceeds the status quo. In contrast, Exp3 and 4 (Fig. 6) assume the presence of psychological factors as a barrier when society evolves. We anticipate that the presence of psychological factors (knowledge and awareness about environment, and personal and subjective norms) could amplify or attenuate households desire to pursue any of three groups of energy actions. In other words, psychological factors could act as a driver and stimulate households, or alternatively they also maybe a barrier preventing households to pursue the actions as explicitly captured by *BENCH* (see Section 3.2.1). In our case – Navarre, Spain – these

psychological factors in general act as a barrier and the number of households that would like to take action reduces. Namely, in Exp2 all agents, for whom it is economically efficient to undertake one of the three energy-related actions, would do that as soon as it becomes profitable. In contrast, in Exp3 and 4 individuals take an action only if the preceding cognitive steps are successful: i.e. a household holds pro-environmental knowledge and awareness about consequences of its actions while being motivated enough to go on with an action that is economically efficient. Table 8 compares the results of Exps 2, 3 and 4. As soon as we add psychological factors, in the first year of trade (2017) there is a significant increase in the number of households' actions. However, later they act as a barrier and fewer households prove to be willing to change their behavior. Fig. 7 illustrates how much energy heterogeneous households could save cumulatively by changing their behavior in the presence of behavioral factors (Exp3 and 4) in comparison to the baseline (Exp2). Thus, the aggregate energy savings at the regional level are reduced by approximately 67% (3790 MWh) due to the impact of psychological barriers in the knowledge activation stage e.g. lack of knowledge and awareness among individuals (Exp3). Assuming that individual decisions are influenced both at the knowledge activation and motivation stages (Exp4), drops the regional energy savings by 80% (4542 MWh) compared to a one-shot individual decision immune to behavioral barriers. In other words, we might be employing just between 20% and 36% of the energy saving potential that individual behavioral changes have to offer. This illustrates the extent and importance of addressing the psychological aspects of potential individual behavioral changes with respect to energy use.

Table 8 reports the distribution of saved electricity (MWh) gained through the energy-related behavior change of heterogeneous households among different income groups and different types of housing. Similar to Exp2, in Exp3 and Exp4 the lower-income households in the income group 2 and the households residing in the "B" energy label dwellings pioneer in saving energy. However, there is a significant reduction in each group in comparison to Exp2.

### 4.3. The role of learning process and social network

Previous experiments study the diffusion of the three types of energy-related behavior changes assuming that household agents are static, do not interact with other households directly (only through aggregated demand that influences the price signals on the market) and do not learn. To explore the impact of raising knowledge, awareness and information diffusion on the region's energy footprint via the

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[6] We also ran a scenario with activating both behavioral processes but keeping both homogeneous. The results indicate there is not significant changes and it has quite a similar trend as the Exp2. Activating the behavior process matters only when it is heterogeneous (Exp3 and 4).
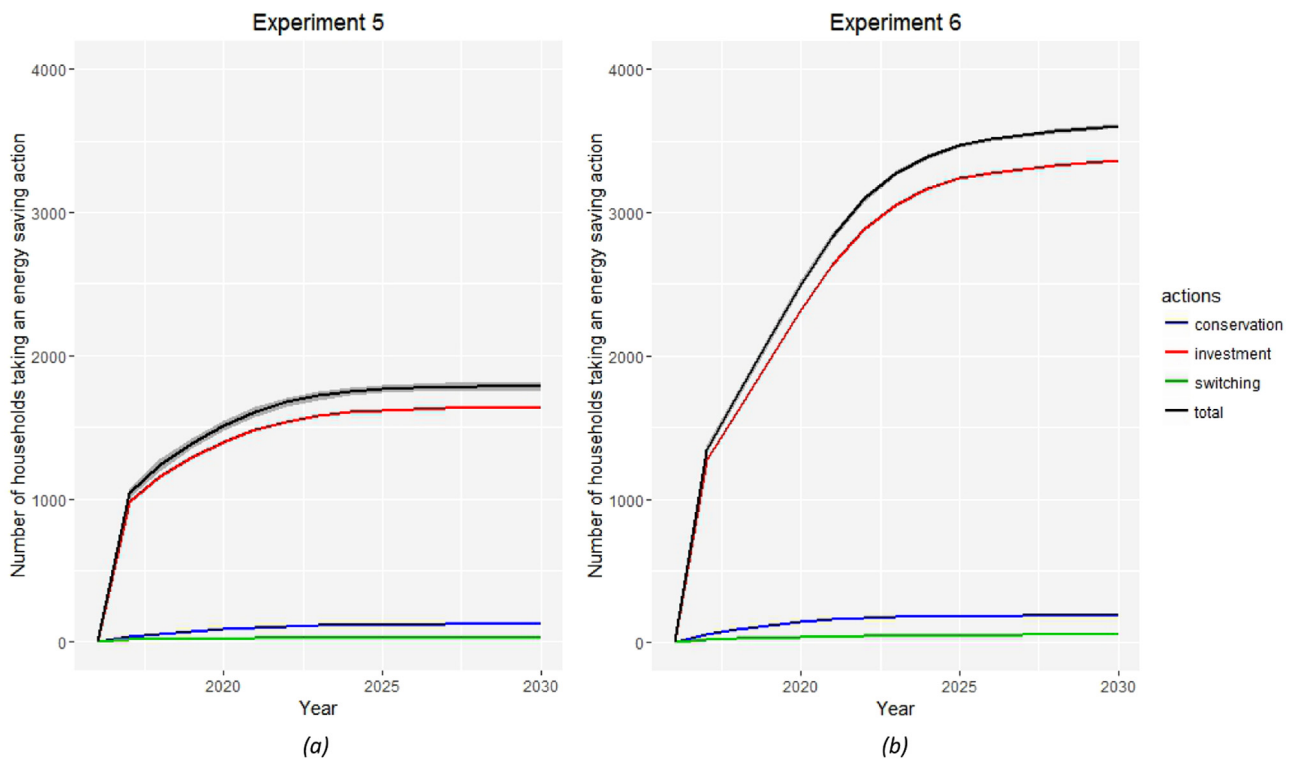
**Fig. 8.** Diffusion of households' energy-related actions (a) in a population of heterogeneous agents learning via their social network during the knowledge activation stage (Exp5), and (b) a population of heterogeneous agents learning via their social network during both knowledge activation and motivation stages (Exp6).

individual learning process and social network we design Exp5 and 6. Here we examine the effect of the learning process and the social network on households' energy-related decisions.

Exp5 extends Exp4 by allowing agents to exchange knowledge and spread awareness about energy and climate through the word of mouth. In other words, households could exchange their information with their neighbors, which can either raise or lower knowledge and awareness regarding LCE. Fig. 8a shows the result of Exp5. The total count of the three types of household actions is significantly higher (1784 households take an action), while there is more intention for investments

rather than for the two other actions. Moreover, the diffusion of household actions does not plateau around year 2025 but continues till year 2030.

Exp6 further extends this learning by introducing opinion dynamics regarding household motivation to act. In this experiment, households learn from each other and this has effect on the knowledge and motivation levels (Fig. 8b). The learning influence could lead to either a decrease or an increase of individual motivation. In our simulation, as households involved in the social network learn from each other, we observed an increase in the diffusion of all 3 actions (3604 households
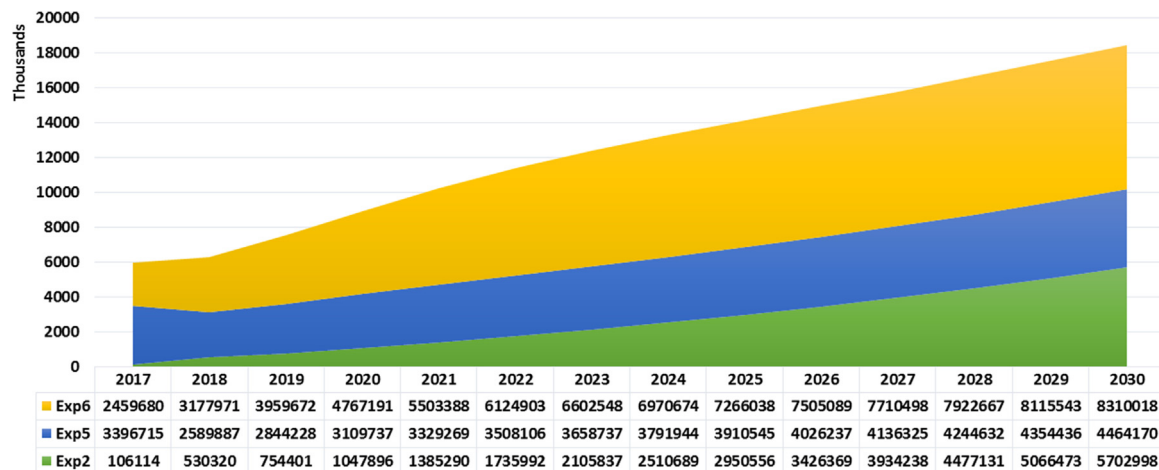


| | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Exp6 | 2459680 | 3177971 | 3959672 | 4767191 | 5503388 | 6124903 | 6602548 | 6970674 | 7266038 | 7505089 | 7710498 | 7922667 | 8115543 | 8310018 |
| Exp5 | 3396715 | 2589887 | 2844228 | 3109737 | 3329269 | 3508106 | 3658737 | 3791944 | 3910545 | 4026237 | 4136325 | 4244632 | 4354436 | 4464170 |
| Exp2 | 106114 | 530320 | 754401 | 1047896 | 1385290 | 1735992 | 2105837 | 2510689 | 2950556 | 3426369 | 3934238 | 4477131 | 5066473 | 5702998 |

**Fig. 9.** Saved energy in kWh (Experiments 5, 6 and Experiment 2 as a benchmark). It shows that adding social network and learning in knowledge activation stage (Exp5) and then in knowledge activation and motivation stages (Exp6) helps households to save more energy by changing their behavior. For instant, following the Exp6 strategy, households could save approximately 3800 MWh more energy.

**Table 9**

Distribution of the climate mitigation efforts among various socio-economic groups and dwelling types, assuming agents learn from each other by exchanging information on knowledge and motivation via social networks (Exp5 and Exp6). MWh (percent (%), a contribution of each individual group in total saved energy).

| Socio-economic groups | | Cumulative saved electricity, in MWh | | | |
|---|---|---|---|---|---|
| | | 2020 | | 2030 | |
| Experiments | | Exp5 | Exp6 | Exp5 | Exp6 |
| Income groups | 1 (< 10) | 533 (11%) | 1051 (12%) | 710 (9%) | 1870 (13%) |
| | *2 (10–30)* | *2192 (44%)* | *3764 (44%)* | *3852 (50%)* | *7205 (49%)* |
| | 3 (30–50) | 1280 (25%) | 2266 (27%) | 2012 (26%) | 3884 (26%) |
| | 4 (50–70) | 629 (12%) | 871 (10%) | 689 (9%) | 1088 (7%) |
| | 5 (70–90) | 211 (4%) | 346 (4%) | 257 (3%) | 462 (3%) |
| | *6 (90–110)* | *37 (1%)* | *99 (1%)* | *37 (0%)* | *102 (1%)* |
| | 7 (> 110) | 150 (3%) | 139 (2%) | 163 (2%) | 139 (1%) |
| Dwelling energy label | A | 1112 (22%) | 2331 (27%) | 2452 (32%) | 5151 (35%) |
| | *B* | *1660 (33%)* | *2764 (32%)* | *2280 (30%)* | *4396 (30%)* |
| | C | 1034 (21%) | 1683 (20%) | 1443 (19%) | 2510 (17%) |
| | D | 514 (10%) | 704 (8%) | 637 (8%) | 1079 (7%) |
| | E | 426 (8%) | 677 (8%) | 519 (7%) | 1127 (8%) |
| | *F* | *284 (6%)* | *378 (4%)* | *394 (5%)* | *487 (3%)* |
| Total (compared to the Exp2 in percent) | | 5031 (331%) | 8537 (562%) | 7722 (91.%) | 14751 (174%) |

in total in Ex6). Thus, the energy conservation and switching propagates to a 5.3% portion of population if learning occurs in two stages as in Exp6 as compared to 3.7% in Exp5. Consequently, spreading the knowledge and motivation regarding energy efficient practices via social networks helps decreasing the regional energy use by 78.2% and 145.7% correspondingly compared to Exp2 (Fig. 9).

Notably, when social learning takes place the uptake of Actions 1–3 continues in all income groups (Table 9) and is most popular among owners of houses with the energy label B, as before (Tables 7 and 8).

### 4.4. Macro impacts of individual energy-related behavioral changes

Fig. 10 summarizes the outcomes of all the experiments in terms of diffusion of energy-related behavioral changes. The significant change in the total number of households deciding to either invest in energy efficient technology, or to conserve energy by changing habits, or to switch to a green energy provider occurs when we add heterogeneity to the awareness (Exp3) and let households interact with each other in a social network (Exp6). Spread of opinions about pro-environmental awareness and motivation among heterogeneous households amplifies the diffusion of behavioral changes in a society. The grey bounds around the curves indicate the uncertainty intervals across 100 repetitions of the same experiment under different random seeds. Comparing the Exp2 (in black) and 6 (in red), we observe that the uncertainty decreases. This has to do with the fact that the micro foundations for agents' attributes, individual behavioral rules and social interactions in *BENCH* become more empirically based fueled by our survey data when moving from Exp 2 to Exp 6.

The pro-environmental individual energy choices and changes in these also have significant economic consequences (Fig. 11). Economic benefits of an individual investment action (Action 1) come from saving energy through employing energy-efficient equipment, e.g. installing solar panels. The investment costs are subtracted from these cumulative benefits to get the net benefits of investment. When individuals change energy use habits (Action 2) their economic benefits come purely from paying a lower energy bill due to more conservative energy consumption. In the case of switching (Action 3) to a green (or greener) energy provider, the economic costs or benefits come from a price difference between green and grey electricity.

Changes in households' energy choices have an impact on their carbon foot-print. Fig. 12 presents the dynamics of the cumulative $CO_2$
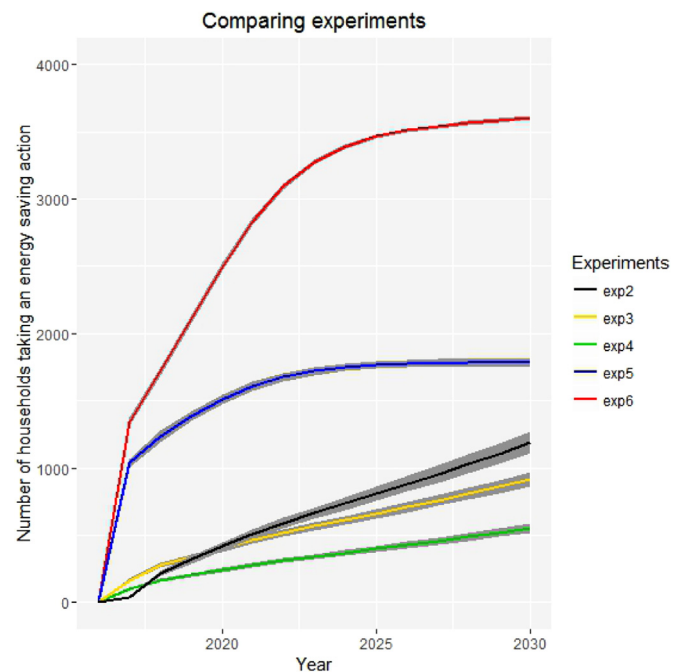
**Fig. 10.** Diffusion of households' energy-related actions measured as the total number of households pursuing either investment, conservation or switching. A baseline Experiment 2 (in black) assumes that households are heterogeneous in economic and housing attributes. Adding psychological factors and, thus behavioral heterogeneity (Exp3 in yellow and Exp4 in green), decreases the total number of households pursuing an energy-related action. However, activating individual learning and social networks, boosts the diffusion of the energy-related actions (Exp5 in blue and Exp6 in red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

emissions saved due to households making investments in solar panels (Action 1). The importance of learning and social interactions is again very pronounced here: the comparison of the baseline Exp2 (black line) and Exp6 (blue line) indicates that social interactions and learning among households boosts the saved $CO_2$ emissions by 82% in 2030.
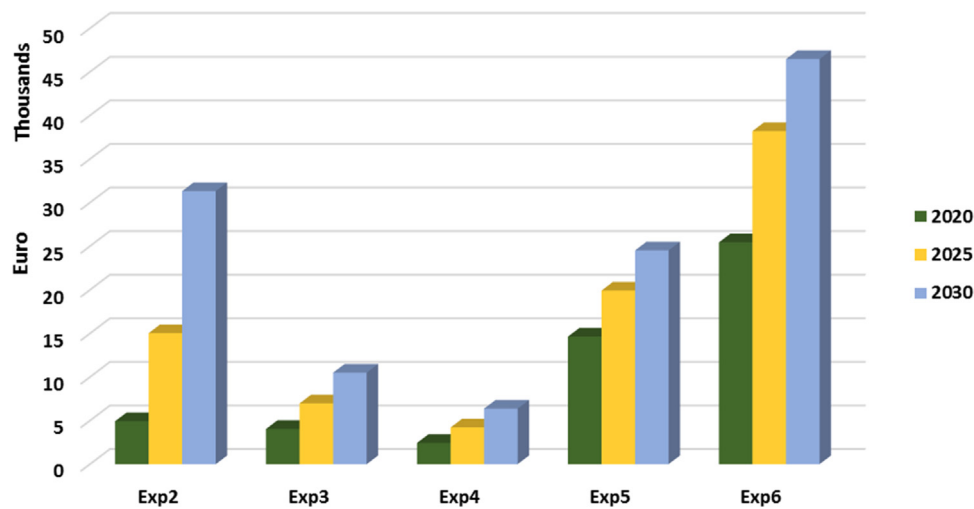
**Fig. 11.** Cumulative/Regional economic net savings as a result of individual households energy-related actions, in euro.
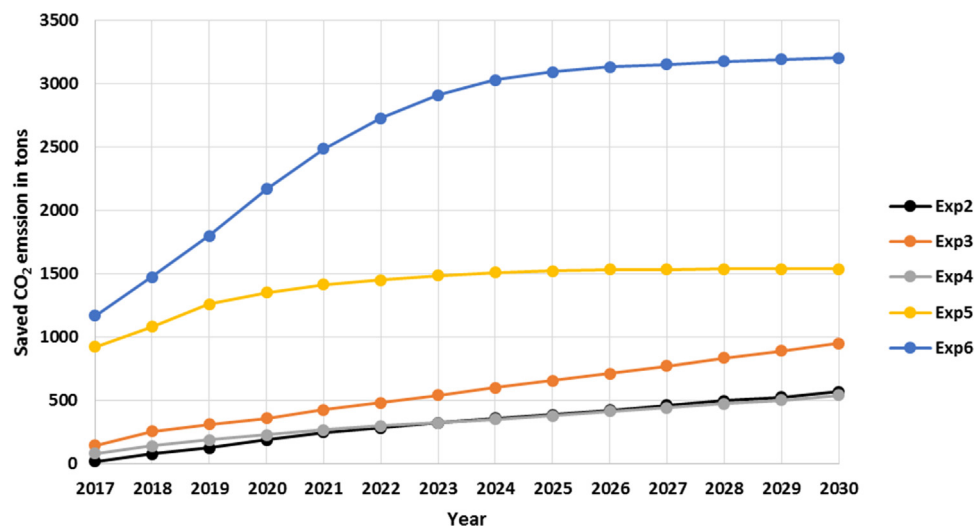


**Fig. 12.** Saved $CO_2$ emissions (in tons) resulting from households energy-related investments (installing solar panels).

## 5. Conclusions and policy Implications

Promoting energy efficient behavior of households is a major challenge and an opportunity for policy-makers. The potential of reducing emissions through behavioral change becomes even more important in the light of the Paris agreement. The scientific challenge is to develop methods to quantitatively assess aggregated impacts of individual changes in energy use given rich behavioral representation of residential energy demand. The paper addresses this challenge by combining an extensive household survey and an empirical ABM, which together form a solid basis for our analysis. This methodological setup permits us to focus on unfolding the behavioral complexity in household energy use in stages, each supported by theory and survey data. In particular, with this approach one can explore such questions as: What are the main behavioral drivers and barriers of energy-related household choices? What is the impact of psychological factors in terms of energy and economic benefits? Can we quantify the impact of social networks in these processes?

The household survey carried out in 2016 in Navarre, Spain is rooted in Norm Activation Theory and elicits information on the types of social interactions, through which people exchange information about energy use. The agent-based BENCH model designed based on this survey allows us to study large-scale regional effects of individual actions and to explore how they may change over time. The model explicitly treats behavioral triggers and barriers at the individual agent level, assuming that energy use decision making is a multi-stage process. We present the results of simulations over 14 years (2016–2030) assuming the business as usual (SSP2) scenario for the model supply side that provides the growth of energy production till 2030. By running several simulation experiments, we add complexity gradually to explore the impact of heterogeneity, psychological factors and learning and social network impacts on energy-related behavioral changes of households and aggregated provincial impacts of these changes.

We report that pro-environmental individual energy choices and behavioral changes depend on social interactions and learning at different stages of households' decision making. Cumulatively these

individual choices have significant economic consequences. Economic benefits of an individual energy-related behavioral change come from their net savings. A household energy bill may decrease due to (i) becoming a partial energy producer (by installing solar power system) and consequently buying less energy from the grid, or (ii) due to changing consumption and conserving energy, or (iii) due to the price difference between green and grey electricity and new price offers by energy suppliers. The results illustrate that spreading knowledge and motivation regarding energy efficient practices via social networks helps decreasing the provincial energy use by 14751 MWh, while increasing the private economic benefits by up to 46000 Euro (Fig. 11) and preventing more than 3200 t of $CO_2$ emissions (Fig. 12). In line with the survey data (Table 5), the *BENCH* simulations show that households in the Navarre region in Spain are likely to invest with energy conservation coming as the second best option and switching to green suppliers being the least preferred choice. These results are contingent on the data used for the model initialization and could be influenced by past policies, such as subsidies for solar in Navarre (del Río and Unruh, 2007). The explorative scenarios in Exp2-Exp6 offer insights on the nature of mechanisms affecting individual choices, their aggregated consequences and the direction of their influence. To increase the predicative power of such behaviorally rich models as BENCH, one should ideally compare aggregated model results with NUTS2 reginal data on investments for 2016 and 2017 (or switching for that matter, conservation is hardly registered in the census or Eurostat data). Given the bottom up nature of ABMs, validation has always been a challenge for this class of models (Carley, 1996; Richiardi et al., 2006; Windrum et al., 2007). While this article offers a solid case on validation micro-foundations of agents' rules, access to the regional level panel data is much desirable to assure validation of the aggregated trends.

These results imply that in the design of energy demand policies aiming at behavioral changes more points-of-action can be discerned than just making the energy saving alternatives more attractive,

financially or otherwise. The presence of behavioral barriers can diminish the potential for energy and emission savings by anywhere between 63% and 80%. Thus, the policy mix should also aim at encouraging and facilitating mutual learning processes for consumers, both with respect to knowledge and motivation. Accompanying information and policy instruments that change values have the potential to greatly contribute to the effectiveness of the more conventional policy approach. Future work may focus on testing an interplay of information and economic policies (subsidies, taxes), calling for more advanced modeling of both demand (e.g. account for discounting) and supply (production costs, tariffs, technological learning). The theoretically and empirically grounded modeling tools such as the agent-based *BENCH* model can serve as a useful instrument to quantify the regional impacts of seemly qualitative and untraceable individual behavioral aspects. Understanding the cumulative impacts of behavioral processes and effect of policies on different socio-economic consumer groups in an artificial regional economy could provide a valuable platform for participatory experiments (Glynn et al., 2017). Such a simulation platform could support engagement of stakeholders. It offers possibilities for decision-makers to explore various policy mixes combining price instruments (subsidies and taxes) with various targeted information policies to amplify the positive effect of individual behavioral changes regarding energy use.

## Acknowledgments

## Appendix A:

In 2016 we ran a household survey over an extensive sample of respondents, N = 800 households, using an online questionnaire in Navarre province, Spain.[7] The questionnaire was distributed using the survey infrastructure – subject pool, sampling methods and contact channels – of Kantar TNS. All the questions that form the basis of this survey are developed by the authors and validated by expert group.[8] Kantar TNS (formerly known as TNS NIPO) has many years of experience with carrying out surveys and assuring that a sample of respondents represents a target population. Table A1 presents basic description of the two populations. The sample represents the population in terms of income and gender. The education level is a bit higher in the sample as compared to the regional population, with the middle group of 'upper secondary and post-secondary' education matching well between the two populations. The data on region is reported based on Eurostat Household Budget Surveys (HBSs), 2016.

We designed the survey based on the environmental psychology literature to identify potential factors of households' energy-related behavioral changes. Specifically, our household survey focuses on factors potentially affecting a decision-making process with respect to the three types of energy-related actions that households typically make: (1) investments to save or produce energy, (2) conservation of energy by changing consumption patterns and habits, and (3) switching to another energy source. The conceptual framework behind the survey based on the NAT (Section 2) assumes three main steps that lead to one of these actions: knowledge activation, motivation, and consideration. Survey questions used to measure the behavioral factors relevant for energy use choices of individual households. Following Tables (A2–A4) show what is the main items in these three main stages -knowledge activation, motivation, and consideration- and how we measured each of these items.**Knowledge and awareness (K)** is measured as a combination of the three main items: *CEE knowledge, CEE awareness and ED awareness* (Section 3.2.1, p 13). To measure each of these items (CEEK, CEEA, EDA) we rely following questions, inspired by the standard measures used in the behavioral literature. Table A2 shows example questions of each knowledge activation items.

**Motivation (M)** as presented in Section 3.2.1 p13, is evaluated based on *Personal norms* (PN) and *Subjective norms* (SN). Table A3 brings example questions that we asked to measure PN and SN.

**Consideration (C)** is measured based on the level of *perceived behavior control* which is differ in three actions (PBC1, PBC2, PBC3) and *Energy-efficient habits and patterns* (HEP). Table A4 shows example questions that we asked households to measure their PBC based on three actions and their conservation habits and patterns.

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[7] Navarre is a province in northern Spain, and consists of 272 municipalities.

[8] Consist of 15 experts: social scientists, statisticians, psychologists, governance and policy scientists, economists, sociologists, agent-based model developers.

**Table A1**

Navarre socio-economic distribution in region and survey sample.

| Factors | | Regional | Survey sample |
|---|---|---|---|
| **Population** | | 637,486 | 800 |
| **Male population (in percentage)** | | 49% | 43% |
| **Average income (thousand Euro per year)** | | 18 | Majority in income group 2 (10–30) |
| **Education levels (in percentage)** | Less than primary, primary and lower secondary education | 27.9 | 16.4% |
| | Secondary education, upper secondary and post-secondary | 23.2 | 22.8% |
| | Tertiary education and more | 48.8 | 60.8% |

**Table A2**

Knowledge activation items.

| **Knowledge and awareness (K)** |
|---|

*Climate-Energy-Economy Knowledge (CEEK)*
   Tick the box that comes closest to your opinion of how true or untrue you think it is.[a]
   Climate change is caused by a hole in the earth's atmosphere.
   …
*Climate-Energy-Economy Awareness (CEEA)*
   To what extent do you agree or disagree with each of the following statements? I believe that…[b]
   Protecting the environment is a means of stimulating economic growth.
   …
*Energy Decision Awareness (EDA)*
   To what extent do you agree or disagree with each of the following statements? I believe that…[b]
   My energy source choice (renewables or fossil fuels) have an impact on the environment
   …

[a] this items measured with Likert scales with labelled end-points (1 = "definitely not true" and 7 = "definitely true").
[b] this items measured with Likert scales with labelled end-points (1 = "strongly disagree" and 7 = "strongly agree").

**Table A3**

Motivation items.

| **Motivation (M)** |
|---|

*Personal Norms (PN)*
   To what extent do you agree or disagree with each of the following statements? I believe that…[a]
   I believe that every time we use coal, oil or gas, we contribute to climate change.
   …
   How likely would you reduce your energy consumption under the following conditions? I would reduce my energy consumption…[b]
   because of personal willingness and self-motivation
   …
*Subjective Norms (SN)*
   How likely would you reduce your energy consumption under the following conditions? I would reduce my energy consumption…[b]
   funding out that my households uses more energy than similar households there is some governmental policies and subsidies (i.e. municipalities, provincial, national level)
   …

[a] this items measured with Likert scales with labelled end-points (1 = "strongly disagree" and 7 = "strongly agree").
[b] this items measured with Likert scales with labelled end-points (1 = "very unlikely" and 7 = "very likely").

**Table A4**
Consideration items.

| Consideration (C) |
| --- |

*Energy-efficient habits and patterns (HEP)[a]*
How often do you perform the following actions in your daily life?
rinse the dishes before putting them in the dish washer
turn off the light in unoccupied room
air dry laundry rather than using a washer dryer
only run full loads when using washing machines or dish washers
…

*Perceived Behavior Control-investment (PBC1)*
To what extent do you agree or disagree with each of the following statements?[b]
I would reduce my energy consumption, if more practical information on how I can invest
  in green energies (e.g. install solar panels) would be available.
If there were subsidies I would pro1duce part of my green energy consumption (e.g. install
  solar panel or fund a wind turbine).
…

*Perceived Behavior Control-Conservation (PBC2)*
To what extent do you agree or disagree with each of the following statements?[b]
I would reduce my energy consumption if energy prices would be higher.
How likely would you reduce your energy consumption under the following conditions? I would
  reduce my energy consumption…[c]
if more practical information on how to reduce energy consumption at home would be
  available
….

*Perceived Behavior Control-Switching (PBC3)*
To what extent do you agree or disagree with each of the following statements?[b]
If I had enough information, it would be easier to switch to green energy
If a renewable/green energy tariff was available at another energy provider, I would
  change my provider.
If a better/cheaper offer was available at another energy provider, I would change my
  provider.
…

[a] this items measured with Likert scales with labelled end-points (1 = "seldom" and 3 = "almost always").
[b] this items measured with Likert scales with labelled end-points (1 = "strongly disagree" and 7 = "strongly agree").
[c] this items measured with Likert scales with labelled end-points (1 = "very unlikely" and 7 = "very likely").

# References

Abrahamse, W., Steg, L., 2009. How do socio-demographic and psychological factors relate to households' direct and indirect energy use and savings? J. Econ. Psychol. 30, 711–720.

Abrahamse, W., Steg, L., 2011. Factors related to household energy use and intention to reduce It: the role of psychological and socio-demographic variables. Hum. Ecol. Rev. 18, 30–40.

Acemoglu, D., Ozdaglar, A., 2011. Opinion dynamics and learning in social networks. Dyn. Games Appl. 1, 3–49.

Adnana, N., Nordina, S.M., Rahmanb, I., 2017. Adoption of PHEV/EV in Malaysia: a critical review on predicting consumer behaviour. Renew. Sustain. Energy Rev. 72.

Ajzen, I., 1980. Understanding Events - Affect and the Construction of Social-Action - Heise, Dr. Contemp Psychol 25, pp. 775–776.

Aliabadi, D.E., Kaya, M., Sahin, G., 2017. Competition, risk and learning in electricity markets: an agent-based simulation study. Appl. Energy 195.

Amouroux, E., Huraux, T., Sempé, F., Sabouret, N., Haradji, Y., 2013. Simulating human activities to investigate household energy consumption. ICAART 2013.

Anatolitis, V., Welisch, M., 2017. Putting renewable energy auctions into action – An agent-based model of onshore wind power auctions in Germany. Energy Policy 110, 394–402.

Armitage, C.J., Conner, M., 2001. Efficacy of the theory of planned behaviour: a meta-analytic review. Br. J. Soc. Psychol. 40, 471–499.

Bamberg, S., Hunecke, M., Blobaum, A., 2007. Social context, personal norms and the use of public transportation: two field studies. J. Environ. Psychol. 27, 190–203.

Bamberg, S., Rees, J., Seebauer, S., 2015. Collective climate action: determinants of participation intention in community-based pro-environmental initiatives. J. Environ. Psychol. 43, 155–165.

Bhattacharyya, S.C., 2011. Energy Economics : Concepts, Issues, Markets and Governance. Springer, London.

Bhushan, N., Albers, C., Steg, L., 2016. Detecting patterns in household electricity consumption after behavioural interventions, In: Proceedings of the 4th European Conference on Behaviour and Energy Efficiency, Coimbra, Portugal.

Bravo, G., Vallino, E., Cerutti, A.K., Pairotti, M.B., 2013. Alternative scenarios of green consumption in Italy: an empirically grounded model. Environ. Modell. Softw. 47, 225–234.

Carley, K.M., 1996. Validating Computational Models, in: University, C.M. (Ed.).

Chappin, E., Afman, M.R., 2013. An agent-based model of transitions in consumer lighting: policy impacts from the E.U. phase-out of incandescents. Environ. Innov. Soc. Transit. 7.

Chappin, E., Dijkema, G., van Dam, K., Lukszo, Z., 2007. Modeling strategic and operational decision-making - An agent-based model of electricity producers. In:

Proceedings of the European Simulation and Modelling Conference 2007, pp. 356–363.

Ciarreta, A., Espinosa, M.P., Pizarro-Irizar, C., 2014. Is green energy expensive? Empirical evidence from the Spanish electricity market. Energy Policy 69, 205–215.

Ciarreta, A., Espinosa, M.P., Pizarro-Irizar, C., 2017. Has renewable energy induced competitive behavior in the Spanish electricity market? Energy Policy 104, 171–182.

Cleveland, C.J., Ayres, R.U., 2004. Encyclopedia of energy. Elsevier Academic Press, Amsterdam; Boston.

De Groot, J.I.M., Steg, L., 2009. Morality and prosocial behavior: the role of awareness, responsibility, and norms in the norm activation model. J. Soc. Psychol. 149, 425–449.

Degroot, M.H., 1974. Reaching a Consensus. J. Am. Stat. Assoc. 69, 118–121.

del Río, P., Unruh, G., 2007. Overcoming the lock-out of renewable energy technologies in Spain: the cases of wind and solar electricity. Renew. Sustain. Energy Rev. 11, 1498–1513.

EC, 2017. Consumer conditions scoreboard, Consumers at home in the single market : 2017 edition. EU Publication.

Faber, J., Schoroten, A., Bles, M., Sevenster, M., Markowska, A., Smit, M., Rohde, C., Dütschke, E., Köhler, J., Gigli, M., Zimmermann, K., Soboh, R., Riet, J., 2012. Behavioural Climate Change Mitigation Options and Their Appropriate Inclusion in Quantitative Longer Term Policy Scenarios, Delft.

Federico, G., Vives, X., 2008. Competition and Regulation in the Spanish Gas and Electricity Markets. Public-Ptivate Sector Research Center, IESE Bussiness School, Madrid, Spain.

Frederiks, E.R., Stennerl, K., Hobman, E.V., 2015. Household energy use: applying behavioural economics to understand consumer decision-making and behaviour. Renew. Sust. Energ. Rev. 41, 1385–1394.

Gerst, M.D., Wang, P., Roventini, A., Fagiolo, G., Dosi, G., Howarth, R.B., Borsuk, M.E., 2013. Agent-based modeling of climate policy: an introduction to the ENGAGE multi-level model framework. Environ. Modell. Softw. 44, 62–75.

Glynn, P.D., Voinov, A.A., Shapiro, C.D., White, P.A., 2017. From data to decisions: processing information, biases, and beliefs for improved management of natural resources and environments. Earth's Future 5, 356–378.

Groeneveld, J., Muller, B., Buchmann, C.M., Dressler, G., Guo, C., Hase, N., Hoffmann, F., John, F., Klassert, C., Lauf, T., Liebelt, V., Nolzen, H., Pannicke, N., Schulze, J., Weise, H., Schwarz, N., 2017. Theoretical foundations of human decision-making in agent-based land use models - A review. Environ. Modell. Softw. 87, 39–48.

Hegselmann, R., Krause, U., 2002. Opinion dynamics and bounded confidence, models, analysis and simulation. J. Artif. Soc. Social. Simul. 5.

Hunt, L.C., Evans, J., 2009. International Handbook on the Economics of Energy. Edward Elgar, Cheltenham, UK ; Northampton, MA.

Iychettira, K.K., Hakvoort, R.A., Linares, P., de Jeu, R., 2017. Towards a comprehensive

policy for electricity from renewable energy: designing for social welfare. Appl. Energy 187, 228–242.

Jackson, J., 2010. Improving energy efficiency and smart grid program analysis with agent-based end-use forecasting models. Energy Policy 38, 3771–3780.

Kahneman, D., 2003. A psychological perspective on economics. Am. Econ. Rev. 93, 162–168.

Kancs, A., 2001. Predicting European enlargement impacts - A framework of interregional general equilibrium. East. Eur. Econ. 39, 31–63.

Karatasou, S., Santamouris, M., 2010. Detection of low-dimensional chaos in buildings energy consumption time series. Commun. Nonlinear Sci. 15, 1603–1612.

Kowalska-Pyzalska, A., Maciejowska, K., Suszczyński, K., Sznajd-Weron, K., Weron, R., 2014. Turning green: agent-based modeling of the adoption of dynamic electricity tariffs. Energy Policy 72, 164–174.

Kumar, S., 2016. Assessment of renewables for energy security and carbon mitigation in Southeast Asia: the case of Indonesia and Thailand. Appl. Energy 163, 63–70.

Lee, J.-S., Filatova, T., Ligmann-Zielinska, A., Hassani-Mahmooei, B., Stonedahl, F., Lorscheid, I., Voinov, A., Polhill, J.G., Sun, Z., Parker, D.C., 2015. The complexities of agent-based modeling output analysis. J. Artif. Soc. Social. Simul. 18, 4.

Malama, A., Makashini, L., Abanda, H., Ng'ombe, A., Mudenda, P., 2015. A Comparative Analysis of Energy Usage and Energy Efficiency Behavior in Low- and High-Income Households: The Case of Kitwe, Zambia. Resources 4.

McKinsey, 2009. Pathways to a Low-Carbon Economy, 2 ed.

Moussaid, M., Brighton, H., Gaissmaier, W., 2015. The amplification of risk in experimental diffusion chains. Proc. Natl. Acad. Sci. USA 112, 5631–5636.

Niamir, L., Filatova, T., 2015. Linking Agent-based energy market with Computable General Equilibrium Model: an Integrated Approach to Climate-Economy-Energy System, In: Proceedings of the 20th WEHIA Conference, Sophia Antipolis, France.

Niamir, L., Filatova, T., 2016. From Climate Change Awareness to Energy Efficient Behaviour, In: Proceedings of the 8th International Congress on Environmental Modelling and Software, Toulouse, France.

Niamir, L., Filatova, T., 2017. Transition to Low-carbon Economy: Simulating Nonlinearities in the Electricity Market, Navarre Region-Spain, Advances in Social Simulation 2015. Springer.

Nyborg, K., Anderies, J.M., Dannenberg, A., Lindahl, T., Schill, C., Schlüter, M., Adger, W.N., Arrow, K.J., Barrett, S., Carpenter, S., Chapin, F.S., Crépin, A.-S., Daily, G., Ehrlich, P., Folke, C., Jager, W., Kautsky, N., Levin, S.A., Madsen, O.J., Polasky, S., Scheffer, M., Walker, B., Weber, E.U., Wilen, J., Xepapadeas, A., de Zeeuw, A., 2016. Social norms as solutions. Science 354, 42–43.

Onwezen, M.C., Antonides, G., Bartels, J., 2013. The norm activation model: an exploration of the functions of anticipated pride and guilt in pro-environmental behaviour. J. Econ. Psychol. 39, 141–153.

Palmer, J., Sorda, G., Madlener, R., 2015. Modeling the diffusion of residential photovoltaic systems in Italy: an agent-based simulation. Technol. Forecast Soc. 99, 106–131.

Pollitt, M.G., Shaorshadze, I., 2013. The Role of Behavioural Economics in Energy and Climate Policy. Handbook on Energy and Climate Change. Edward Elgar.

Poortinga, W., Steg, L., Vlek, C., 2004. Values, environmental concern, and environmental behavior - A study into household energy use. Environ. Behav. 36, 70–93.

Rai, V., Henry, A.D., 2016. Agent-based modelling of consumer energy choices. Nat. Clim. Change 6, 556–562.

Rai, V., Robinson, S.A., 2015. Agent-based modeling of energy technology adoption: empirical integration of social, behavioral, economic, and environmental factors. Environ. Modell. Softw. 70, 163–177.

Richiardi, M., Leombruni, R., Saam, N.J., Sonnessa, M., 2006. A common protocol for agent-based Social simulation. J. Artif. Soc. Social. Simul. 9.

(a) Salies, E., Lin, B., Jiang, Z., 2012. Designation and influence of household increasing block electricity tariffs in China. Energy Policy 42, 164–173(b) Salies, E., Lin, B., Jiang, Z., 2012. How biased is the measurement of household's loss. Energy Policy 48, 843–845.

Sarkis, A.M., 2017. A comparative study of theoretical behaviour change models predicting empirical evidence for residential energy conservation behaviours. J. Clean. Prod. 141, 526–537.

Schwartz, S.H., 1977. Normative influences on Altruism1. In: Leonard, B. (Ed.), Advances in Experimental Social Psychology. Academic Press, pp. 221–279.

Siagian, U.W.R., Yuwono, B.B., Fujimori, S., Masui, T., 2017. Low-carbon energy development in indonesia in alignment with Intended Nationally Determined Contribution (INDC) by 2030. Energies 10.

Stern, P.C., 1992. What psychology knows about energy-conservation. Am. Psychol. 47, 1224–1232.

Stern, P.C., Janda, K.B., Brown, M.A., Steg, L., Vine, E.L., Lutzenhiser, L., 2016. Opportunities and insights for reducing fossil fuel consumption by households and organizations. Nat. Energy 1.

Tesfatsion, L., 2006. Agent-based computational economics: a constructive approache to economic theory. In: Tesfatsion, L., Judd, K.L. (Eds.), Handbook og Computational Economics. Amsterdam, The Netherlands, North-Holland.

UNEP, 2017. The Emissions Gap Report 2017. United Nations Environment Programme.

Varian, H.R., 1992. Microeconomic Analysis, 3rd ed. Norton, New York.

Wall, R., Devine-Wright, P., Mill, G.A., 2007. Comparing and combining theories to explain proenvironmental intentions - The case of commuting-mode choice. Environ. Behav. 39, 731–753.

Wilensky, U., 1999. NetLogo.

Wilson, C., Dowlatabadi, H., 2007. Models of decision making and residential energy use. Annu. Rev. Environ. Resour. 32, 169–203.

Windrum, P., Fagiolo, G., Moneta, A., 2007. Empirical validation of agent-based models: alternatives and prospects. J. Artif. Soc. Social. Simul. 10.

Abdmouleh, Z., Gastli, A., Ben-Brahim, L., 2018. Survey about public perception regarding smart grid, energy efficiency & renewable energies applications in Qatar. Renewable and Sustainable Energy Reviews 82, 168–175.

Ameli, N., Brandt, N., 2015. Determinants of households' investment in energy efficiency and renewables: evidence from the OECD survey on household environmental behaviour and attitudes. Environ Res Lett 10.

Buchanan, K., Banks, N., Preston, I., Russo, R., 2016. The British public's perception of the UK smart metering initiative: Threats and opportunities (vol 91, pg 87, 2016). Energ Policy 93, 149 -149.

Buryk, S., Mead, D., Mourato, S., Torriti, J., 2015. Investigating preferences for dynamic electricity tariffs: The effect of environmental and system benefit disclosure. Energ Policy 80, 190–195.

Cao, J., Choi, C.H., Zhao, F., 2017. Agent-based modeling of the adoption of high-efficiency lighting in the residential sector. Sustainable Energy Technologies and Assessments 19, 70–78.

Ceschi, A., Dorofeeva, K., Sartori, R., Dickert, S., Scalco, A., 2015. A Simulation of Householders' Recycling Attitudes Based on the Theory of Planned Behavior. Trends in Practical Applications of Agents, Multi-Agent Systems and Sustainability: The Paams Collection. 372, 177–184.

Chappin, E., 2012. Agent-based Simulation of Energy Transition, International Engineering Systems Symposium. Delft University of Technology, Delft, the Netherlands.

Chappin, E.J.L., Dijkema, G.P.J., 2007. An agent based model of the system of electricity production systems: Exploring the impact of CO2 emission-trading. 2007 Ieee International Conference on System of Systems Engineering, Vols 1 and 2, 277-281.

de Koning, K., Filatova, T., Bin, O., 2017. Bridging the Gap Between Revealed and Stated Preferences in Flood-prone Housing Markets. Ecol Econ 136, 1–13.

Deng, G., Newton, P., 2017. Assessing the impact of solar PV on domestic electricity consumption: Exploring the prospect of rebound effects. Energ Policy 110, 313–324.

Filatova, T., Parker, D.C., van der Veen, A., 2011. The Implications of Skewed Risk Perception for a Dutch Coastal Land Market: Insights from an Agent-Based Computational Economics Model. Agricultural and Resource Economics Review 40, 405–423.

Gallo, G., 2016. Electricity market games: How agent-based modeling can help under high penetrations of variable generation. The Electricity. Journal 29, 399 -346.

Gotts, N.M., Polhill, J.G., 2017. Experiments with a Model of Domestic Energy Demand. Journal of Artificial Societies and Social Simulation 20, 11.

Gotts, N.M., Polhill, J.G., Law, A.N.R., 2003. ASPIRATION LEVELS IN A LAND USE SIMULATION. Cybernetics and Systems 34, 663–683.

Haer, T., Botzen, W.J.W., Aerts, J.C.J.H., 2016. The effectiveness of flood risk communication strategies and the influence of social networks-Insights from an agent-based model. Environmental Science and Policy 60, 44–52.

He, X., Reiner, D., 2017. Why consumers switch energy suppliers: The role of individual attitudes. Energ J 38, 25–53.

Jager, W., Janssen, M.A., De Vries, H.J.M., De Greef, J., Vlek, C.A.J., 2000. Behaviour in commons dilemmas: Homo economicus and Homo psychologicus in an ecological-economic model. Ecol Econ 35, 357–379.

Kamara-Esteban, O., Sorrosal, G., Pijoan, A., Castillo-Calzadilla, T., Iriarte-Lopez, X., Macarulla-Arenaza, A.M., Martin, C., Alonso-Vicario, A., Borges, C.E., 2016. Bridging the Gap between Real and Simulated Environments: A Hybrid Agent-Based Smart Home Simulator Architecture for Complex Systems, Proceedings - 13th IEEE International Conference on Ubiquitous Intelligence and Computing, 13th IEEE International Conference on Advanced and Trusted Computing, 16th IEEE International Conference on Scalable Computing and Communications, IEEE International Conference on Cloud and Big Data Computing, IEEE International Conference on Internet of People and IEEE Smart World Congress and Workshops, UIC-ATC-ScalCom-CBDCom-IoP-SmartWorld 2016, pp. 220-227.

Kiesling, E., Gunther, M., Stummer, C., Wakolbinger, L.M., 2012. Agent-based simulation of innovation diffusion: a review. Cent Eur J Oper Res 20, 183–230.

Krömker, D., Eierdanz, F., Stolberg, A., 2008. Who is susceptible and why? An agent-based approach to assessing vulnerability to drought. Reg Environ Change 8, 173–185.

Liu, X., Li, X., Anthony, G.-O.Y., 2006. Multi-agent systems for simulating spatial decision behaviors and land-use dynamics. Science in China Series D: Earth Sciences 49, 1184–1194.

McDaniel, T.M., Groothuis, P.A., 2012. Retail competition in electricity supply-Survey results in North Carolina. Energ Policy 48, 315–321.

Mills, B., Schleich, J., 2012. Residential energy-efficient technology adoption, energy conservation, knowledge, and attitudes: An analysis of European countries. Energ Policy 49, 616–628.

Parker, D.C., Manson, S.M., Janssen, M.A., Hoffmann, M.J., Deadman, P., 2003. Multi-Agent Systems for the Simulation of Land-Use and Land-Cover Change: A Review. Ann Assoc Am Geogr 93, 314–337.

Polhill, G., Gotts, N., 2017. How precise are the specifications of a psychological theory? Comparing implementations of lindenberg and steg's goal-framing theory of everyday pro-environmental behaviour. Advances in Intelligent Systems and Computing 341–354.

Rangoni, R., Jager, W., 2017. Social dynamics of littering and adaptive cleaning strategies explored using agent-based modelling. JASSS 20.

Rommel, J., Sagebiel, J., Müller, J.R., 2016. Quality uncertainty and the market for renewable energy: Evidence from German consumers. Renew Energ 94, 106–113.

Rounsevell, M.D.A., Arneth, A., Alexander, P., Brown, D.G., de Noblet-Ducoudré, N., Ellis, E., Finnigan, J., Galvin, K., Grigg, N., Harman, I., Lennox, J., Magliocca, N., Parker, D., O'Neill, B.C., Verburg, P.H., Young, O., 2014. Towards decision-based global land use models for improved understanding of the Earth system. Earth Syst. Dynam 5, 117–137.

Schwarz, N., Ernst, A., 2009. Agent-based modeling of the diffusion of environmental

innovations - An empirical approach. Technol Forecast Soc 76, 497–511.

Thøgersen, J., 2017. Housing-related lifestyle and energy saving: A multi-level approach. Energ Policy 102, 73–87.

Tran, M., 2012. Agent-behaviour and network influence on energy innovation diffusion. Commun Nonlinear Sci 17, 3682–3695.

van Duinen, R., Filatova, T., Jager, W., van der Veen, A., 2016. Going beyond perfect rationality: drought risk, economic choices and the influence of social networks. Ann Regional Sci 57, 335–369.

Vasiljevska, J., Douw, J., Mengolini, A., Nikolic, I., 2017. An agent-based model of electricity consumer: Smart metering policy implications in Europe. JASSS 20.

Weidlich, A., Veit, D., 2008. A critical survey of agent-based wholesale electricity market models. Energ Econ 30, 1728–1759.