Behavioural Climate Change Mitigation

from individual energy choices to demand-side potential

Leila Niamir

BEHAVIOURAL CLIMATE CHANGE MITIGATION

from individual energy choices to demand-side potential

Leila Niamir

Graduation Committee:

Chair	
Prof. dr. T.A.J. Toonen	University of Twente
Promoters	
Prof. dr. T. Filatova	University of Twente
Prof. dr. J.T.A. Bressers	University of Twente
Co-promoter	
Prof. dr. A. Voinov	University of Technology Sydney
Members	
Prof. dr. ir. P. Herder	Delft University of Technology
Prof. dr. R. Sauerborn	Heidelberg University
Prof. dr. M.A. Heldeweg	University of Twente
Dr. M.J. Arentsen	University of Twente
Dr. O. Ivanova	PBL
Dr. W. Jager	University of Groningen

SEVENTH FRAMEWORK PROGRAMME

Netherlands Organisation for Scientific Research

This work was supported by the EU FP7 COMPLEX (Knowledge Based Climate Mitigation Systems for a Low Carbon Economy) Project (No. 308601) and The Netherlands Organisation for Scientific Research (NWO) YSSP Grant (No. 0539.600.101).

Publisher: Gildeprint, Enschede
Cover design: Farideh Shahbazi, Jaleh Niamir
ISBN: 978-90-365-4712-3
DOI: 10.3990/1.9789036547123

MIX From responsible sources FSC® C006249 FSC www.fsc.org

BEHAVIOURAL CLIMATE CHANGE MITIGATION

FROM INDIVIDUAL ENERGY CHOICES

TO DEMAND-SIDE POTENTIAL

DISSERTATION

to obtain
the degree of doctor at the University of Twente,
on the authority of the rector magnificus,
prof. dr. T.T.M. Palstra,
on account of the decision of the graduation committee,
to be publicly defended
on Friday the 1st of February 2019 at 12:45 hrs

by
Leila Niamir
born on the 20th of February 1988
in Tehran, Iran.

This dissertation is approved by

Prof. dr. T. Filatova
Prof. dr. J.T.A. Bressers
Prof. dr. A. Voinov

Acknowledgements

I have finally reached the end of the road that I started in 2014. It was an amazing journey. All the ups and downs helped me to discover other perspectives in life. I knew it would be hard and would need a lot of effort but now I know that it needed encouragement and support most of all. I would like to thank several people who, in various ways, played an important role throughout this journey.

Firstly, I would like to thank my three promoters who gave me the opportunity to pursue my goal. Tatiana, thank you for steering my research in the right direction. I started my scientific career with you and I have learned a lot from you. Thanks for making me a stronger person. Hans, you were always more than my boss and promoter, as you were always caring and understanding when I needed it the most. Thanks for your great advises and constant support. Alexey, I have always appreciated your great comments on my research and your keen eye for clarity in scientific writings. I would never forget your sentence "don't take it personally and don't give up!" when I was upset for my very first grant proposal rejection. I didn't and it got me where I'm standing today.

During these years, I was lucky to have the chance to visit several amazing research institutes and meet a great number of fantastic scientists. These people deserve a huge "thank you" because I have learned a lot from them.A big thanks goes to Dr. Olga Ivanova and Dr. Gregor Kiesewetter who gave me opportunities to advance my PhD research and offered their help and advice whenever I needed. I am very grateful for all your support. Olga, thank you for welcoming me in your team at PBL. I very much enjoyed my visits to PBL, our meetings and great collaborations. I have learned so much from you as you patiently described the economics concept that appeared exotic for me. Gregor, you are one of the best supervisors that I have ever had. First time, we met at iEMSs 2016 conference, where I presented my first PhD paper. There, you encouraged me to apply for Young Scientists Program at IIASA. The next summer, you along with Fabian and Wolfgang turned to be my YSSP supervisory team. I enjoyed and learned from every second of our long meetings and discussions. Being in IIASA and meeting and collaborating with fantastic team of scientists opened my eyes to the real science world. That's why I keep retuning there every now and then. So get ready for my next visit! I also would like to thank IIASA AIR program colleagues, specially Zig, Markus, Lena, Peter, Janusz and Carmen for all our great meetings, nice chats, and interesting lunch times. My global YSSPer2017 family, you are all awesome! I am pretty sure we will cross paths very soon again. I also would like to express my deep gratitude to Dr. Elena Rovenskaya, Prof. Dr. Brian Fath, Prof. Dr. Arnulf Grubler, Dr. Nils Johnson, Dr. Joeri Rogelj for our fruitful meetings and discussions during my stay at IIASA. You all inspired me very much to follow my ambitions. My PBL colleagues: Moustafa, Trond, Iason, and Mark thank you for all our chats, lunch discussions which made me feel welcomed during my PBL visits. My lovely Global Environments Network family, thank you all for our amazing and unforgettable time in UK. Special thanks to Gary and Susannah who kindly supported and facilitated my participation in this summer program, and Wenjing for our endless philosophical and scientific discussions.

I also would like to express my appreciation to all my friends and colleagues in the Netherlands. Because of you, Enschede felt like home. A special thank you goes to Dr. Johan van der Burgh for all his advice and guidance. John you are an amazing mentor. My former and current colleagues at the Department of Governance and Technology for Sustainability (CSTM), thank you for making here a nice research environment and for your great friendships and supports. In particular, I would like to thank my officemates and dear friends Imke, Ewert, and Koen for the pleasant company, kind support, our coffee and lunch times, and lunch walks. A big thanks goes to

Barbera van Dalm who always kindly supported me in dealing with all the bureaucracy and being patient and helpful at all time. My ITC family, thank you for all your supports and encouragements. ITC library turned to be my second home and a cosy place to work peacefully. Special thanks to Carla and Marga who always welcomed me with a big smile and supported me kindly when I needed. My PoF (Physics of Fluids) family, you are great. I very much enjoyed my time with you guys. Thank you Sander Huisman for introducing me to these amazing people and your great friendship. My Iranian friends: Elham, Ali, Mozhdeh and Morteza, Mitra and Siavash, Alireza, Hassan, Amir, Hengameh, Mohammadreza, and Sina thank you all for the nice times that we created together and not letting me to feel homesick.

My heartfelt appreciation and love goes to my parents. Jaleh and Iraj, I can't describe your never ending love and generosity. You have always supported me to achieve my goals in life, you were my strength, and you gave me wings to fly. With you, nothing can stop me in life. Aidin, you are the best brother, greatest friend, kindest supporter, and strictest mentor I could ever wished for. With you, I always feel stronger. My lovely sister-in-low, Maral, I would never forget your great supports and kind encouragements. You have always brought a big smile on my face and turned my anger and tears to laughter. With you, I am the happiest sister!

Leila Niamir

Enschede,
December 2018

Table of Contents

Chapter 1:

GENERAL INTRODUCTION

1.1. Climate change mitigation

Weather patterns are changing, sea levels are rising, weather events are becoming more extreme, and greenhouse gas emissions are now at their highest levels in history*. Climate change is affecting every individual in every city on every continent. It imposes adverse effects on people, communities, and countries, disrupting regional and national economies.

Global carbon emissions from fossil fuels stand at almost 37 $GtCO_2$ per year and have grown by an average of 2.4% per year so far this century (Le Quere et al., 2018; Wilson and Staffell, 2018). Climate change mitigation refers to efforts to reduce or prevent emissions of greenhouse gases to limit the magnitude of long-term climate change. Mitigation may be achieved by switching to low-carbon energy sources and new technologies, expanding forests and other carbon sinks, improving the energy efficiency of equipment, or changing management practices and consumer behaviour. Therefore, climate change mitigation should take a multifaceted approach in its efforts to help countries move toward climate-resilient and low-emission futures. An emissions trading system, renewable energy standards, and other instruments have been developed to reduce emissions on the production side. Although economic incentives can be effective mechanisms for producers and are relatively easy to implement, mechanisms to affect demand-side emissions are potentially more complicated.

The United Nations climate activities have expanded in their efforts to limit the global temperature increase to 1.5 °C above pre-industrial levels†. However, making decisions about sustainable development and climate

* Climate Change – United Nations Sustainable Development, https://www.un.org/sustainabledevelopment/climate-change-2/

† United Nations Climate Change Conferences: COP21-23

change mitigation is no longer the sole purview of governments. There is an increasing shift in the literature towards a more inclusive concept of governance, which includes the contributions of various levels of government and non-governmental actors, as well as civil society. Households are now being recognised as agents of change, putting the challenge of behavioural change among energy consumers upfront.

1.2. Demand-side solutions for climate change mitigation

Anthropogenic climate change – the most urgent among global challenges – refers to the combustion of fossil fuels and the resulting atmospheric emissions, primarily of CO_2 caused by human activity (IPCC, 2014a; Stern et al., 2016a). This can affect planetary systems at all geographical scales and stretch over centuries. In the last few years, the discussions about climate change strongly stress the importance of demand-side solutions and shifts to transdisciplinary and bottom-up approaches in assisting climate mitigation efforts worldwide (Anderson et al., 2014; Creutzig et al., 2016; Creutzig et al., 2018b; Ebeling and Lotz, 2015; Grubler et al., 2018; Stern, 2016; Stern et al., 2016c). Improving education and raising awareness and human/institutional capacity on climate change mitigation is one of the targets of the UN Sustainable Development Goals (SDG13).

Moving away from fossil fuels is set as a key mitigation strategy (IPCC, 2014a; Peters et al., 2017). However, this needs a technological change along with the development of low-emission and low-consumption energy sources; it also requires social movements. Individuals play an essential role in bottom-up social movements transforming energy systems. By taking energy decisions, individuals affect more than their direct energy consumption. By being members of different social networks –

neighbourhood, family, school, friends, and colleagues – individual energy choices influence the decisions of others.

1.2.1. Individual behavioural change

Individual energy behaviour, especially when amplified through social context, shapes energy demand and, consequently, carbon emissions. By changing their behaviours, individuals can play an essential role in the transformation process towards a low-carbon society and global emissions reduction. International and national commitments will be more achievable if interventions take into account key psychological, social, cultural and organisational factors that influence energy choices, along with factors of an infrastructural, technical and economic nature. Broader engagement of social and behavioural sciences is needed to identify promising opportunities for reducing fossil fuel consumption.

Behavioural changes regarding individual energy use take different forms (Table 1.1). Individuals can invest: either big, such as in solar panels and house insulation, or small, such as in buying energy-efficient appliances (A++ washing machines or low-wattage light bulbs). Alternatively, individuals may save energy by changing their daily routines and habits: by adjusting their thermostat or by switching off the extra lights. Finally, individuals could switch to a supplier that provides green(er) energy.

***Table 1.1**: Individual behavioural changes regarding energy use*

Individuals' energy behaviours	Empirical evidence
Investment Installing a solar power system Installing thermal solar power system Insulation: roof, floor, wall, … Installing efficient appliances Installing smart meters	Mohandes et al. (2019); Abdmouleh et al. (2018); Cabeza et al. (2018); Seebauer (2018); Deng and Newton (2017); Buchanan et al. (2016); Rai and Henry (2016); Buryk et al. (2015); Ameli and Brandt (2015); Rai and Robinson (2015); Tran (2012); Chappin et al. (2007)
Energy conservation Turn off extra devices Consciously use less electricity Run only fully loaded washing machines Tolerate lower (higher) temperatures in winter (summer)	Hess et al. (2018); Jia et al. (2018); Nakano et al. (2018); Rosenow et al. (2018); Thøgersen (2018); Thøgersen (2017); Amouroux et al. (2013); Faber et al. (2012); Mills and Schleich (2012)
Switching supplier Switch from a conventional to a green supplier Switch to greener supplier	Katz et al. (2018); He and Reiner (2017); Rommel et al. (2016); Yang (2014); McDaniel and Groothuis (2012); Tran (2012)

Together, these individual choices impact aggregated energy consumption and carbon footprints. Understanding why, how and when households decide to pursue these choices is vital in assessing climate mitigation policies. Social sciences suggest a number of alternative approaches to conceptualising how people make decisions.

Rational decision-making

The traditional approach to understanding individual decision-making is based on the rational economic model or classical decision-making theory

(Bhattacharyya, 2011; Buchanan and Huczynski, 2016; Hunt and Evans, 2009). Decision-making refers to making choices among alternative courses of action, which may also include inaction. The neoclassical approach assumes that rational fully informed individuals optimise their utility by making the best decision among a wide range of options. The optimal decision is constrained by a household's budget. Theoretical models often assume a representative agent to allow for aggregation. If heterogeneity is introduced, it usually comes in the form of three to five representative income groups.

Empirical research goes a step beyond purely constrained utility maximisation. The essential role of individual socio-economic characteristics in energy investments – e.g., technology adoption – is acknowledged in several studies. For example, it has been shown that income and probability of investing in energy-efficient technologies are positively correlated (Ameli and Brandt, 2015; Long et al., 2018; Mills and Schleich, 2009; Sardianou and Genoudi, 2013). Some studies report that individuals with a higher level of education are more likely to adopt energy-efficient technologies (Michelsen and Madlener, 2012; Mills and Schleich, 2010, 2012; Sardianou and Genoudi, 2013). The evidence on the impact of age is mixed. Mahapatra and Gustavsson (2008); Michelsen and Madlener (2012); Mills and Schleich (2012); Mills and Schleich (2009) suggest that there is a negative correlation, while other studies report that middle-aged people are more active in this regard compared to youngsters (Sardianou and Genoudi, 2013).

Some studies highlighted the importance of dwelling characteristics for individual choices. The tenure status of the residence – owner or renter – appears to be an important driver of using energy-efficient technologies. In particular, owners are more likely than renters to invest in insulation and energy-efficient appliances (Ameli and Brandt, 2015; Davis, 2010; Gillingham et al., 2012). Some studies (Ameli and Brandt (2015); Michelsen and Madlener (2012); Mills and Schleich (2009)) also highlight other dwelling characteristics such as type (e.g., detached-house, apartment), size, location (e.g., rural, urban), and age (Ameli and Brandt, 2015; Hamilton et al., 2013; Michelsen and Madlener, 2012; Mills and Schleich, 2009).

Behavioural change theories

The emotional parts of individuals' brains still have a strong influence on their behaviours and choices. Thus, making a practical decision goes beyond just obtaining full information, which is impractical to estimate given the uncertainties in the consequences considered. Empirical studies in psychology and behavioural economics show that individual choices and behaviours 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; Niamir et al., 2018b; Pollitt and Shaorshadze 2013; Stern, 2013; Stern, 1992; Wilson and Dowlatabadi, 2007). This implies that people do not necessarily 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.

Individual behavioural change is a multi-stage process. In application to environmental and energy-related choices, three behavioural change theories are commonly applied: theory of planned behaviour (TPB), norm activation theory (NAT), and value–belief–norm (VBN) theory. TPB, formulated by Ajzen (1980a) based on the theory of reasoned action, is one of the most influential theories in social and health psychology and is used in many environmental studies (Armitage and Conner, 2001; Onwezen et al., 2013). TPB assumes that an intention to change behaviour is shaped by three main factors: human attitude towards a specific behaviour, subjective norms, and perceived behavioural control. NAT, initially developed by Schwartz (1977), operates in the context of altruistic and environmentally friendly behaviour. It is mostly focused on anticipating pride in doing the 'right' thing and on studying the evolution of feelings of guilt. VBN theory (Stern, 2000; Stern et al., 1999) explains environmental behaviour and 'good intentions' such as willingness to change behaviour (Nordlund and Garvill, 2003; Steg and Vlek, 2009; Stern et al., 1999), environmental citizenship (Stern et al., 1999), policy acceptability (De Groot and Steg, 2009; Steg et al., 2005), etc. In summary, TPB is focused on gain goal-frames, while NAT and VBN concentrate on normative goal-frames (Steg and Vlek, 2009). Some behavioural factors are common across these alternative conceptualisations of individual pro-environmental choices. While some empirical studies aim to test which of the theories better explain choices, others attempt to combine these theories to offer a more holistic view on individual decision-making (Ameli and Brandt, 2015; Bamberg et al., 2015). Table 1.2 presents the diffusion of behavioural theories used in environmental and energy studies.

Table 1.2: *Behavioural theories*

Theory/field	Energy studies	Other environmental studies
TPB	Zahedi et al. (2019); Adnan et al. (2018); Di Falco and Sharma (2018); Du et al. (2018); Kar and Zerriffi (2018); Kuo et al. (2018); Adnan et al. (2017); Cooper (2017); Raihanian Mashhadi and Behdad (2017); Park and Kwon (2017); Rai and Henry (2016); Rai and Robinson (2015); Faiers and Neame (2006)	Al Mamun et al. (2018); Hao et al. (2018); Li and Hu (2018); Shin and McCann (2018); Gao et al. (2017); Tan et al. (2017); Timm and Deal (2017); Ceschi et al. (2015); Kiesling et al. (2012); Schwarz and Ernst (2009)
NAT	Niamir et al. (2018b); Nordlund et al. (2018) Niamir and Filatova (2016); Bator et al. (2014); Zhang et al. (2013a); Matthies et al. (2011); Nordlund and Garvill (2003)	Wang et al. (2018); van der Werff and Steg (2015); Onwezen et al. (2013); Zhang et al. (2013b); De Groot and Steg (2009)

VBN	Abrahamse and Steg (2011)	Steg (2016); Steg et al. (2005); Poortinga et al. (2004)
Combination of theories	Liu et al. (2017); Sarkis (2017); Imanina et al. (2016); Botetzagias et al. (2014); Abrahamse and Steg (2009)	Olsson et al. (2018)

Abrahamse and Steg (2009) applied NAT and TPB to study the extent to which socio-demographic and psychological factors are related to individuals' energy use and savings. They argue that NAT variables such as awareness and personal norms are more significant than TPB variables such as attitudes and perceived behaviour control in explaining energy behaviour. In addition, they mention that different types of energy methods appear to be related to different sets of variables. Onwezen et al. (2013) also consider the NAT and TPB integrated framework to get better insights into the role of pride and guilt in pro-environmental behaviour. Adnana et al. (2017) use the extended TPB in predicting individuals' intentions towards the adaptation of electric and plug-in hybrid vehicles. In their framework, the three core components of TPB – attitudes, subjective norms, and personal norms – are used. Also, they add some socio-demographic control variables to test their impacts on intentions to adapt. Sarkis (2017) shows the importance of using behavioural change and decision-making models in illustrating consumers' energy behaviours by comparing TPB and VBN. He argues that using any theoretically based framework to understand human behaviour is inheritably linked to individual psychological variables – beliefs, norms, and attitudes – which should be tested empirically. However, concrete studies of residential energy-related behavioural changes, verified by detailed empirical data, are rare (Bhushan et al., 2016; Stern et al., 2016b).

1.2.2. Assessment tools

In the last decade, a variety of macro-economic models and assessment tools (Crespo Cuaresma, 2017; Fricko et al., 2017; Jiang and O'Neill, 2017; Kc and Lutz, 2017; Rao et al., 2017; van Vuuren et al., 2017) emerged and were predominately used to support climate change policy debates, particularly in the economics of climate change mitigation – e.g., GAINS[*], PRIMES[†] and GLOBIOM[‡] models. These comprehensive models address a broad range of policy issues by simulating the connections across all sectors of the economy, which requires theoretical and data consistency. In a multi-sectoral model, computable general equilibrium (CGE) simulation begins with a general equilibrium condition followed by a policy shock – e.g., introduction of an emission trading system. There are also partial equilibrium models which are widely used in sector-specific policy analyses (Kotevska et al., 2013; Latta et al., 2013). These quantitative tools and assessment frameworks, which range from macro-economic assessments and cross-sectoral impacts (Kancs, 2001; Siagian et al., 2017) to detailed micro-simulation models for a specific technology (Bhattacharyya, 2011; Hunt and Evans, 2009) may not be sufficient to provide reliable information for policymakers. Much can be done to make the assumptions in macro-economic and integrated assessment models more realistic concerning the scale and nature of damage (Stern, 2016). These models usually assume that economic agents form a representative group(s), have perfect access to information and adapt instantly and rationally to new situations, maximising their long-run personal advantage. In reality, people make decisions shaped

---

[*] https://ec.europa.eu/clima/sites/clima/files/strategies/analysis/models/docs/gains_en.pdf

[†] https://ec.europa.eu/clima/sites/clima/files/strategies/analysis/models/docs/primes_model_2013-2014_en.pdf

[‡] https://ec.europa.eu/clima/sites/clima/files/strategies/analysis/models/docs/globiom_en.pdf

by their diverse preferences, socio-economic conditions, behavioural biases and social peer influence (Farmer and Foley, 2009).

How can one account for this behavioural uncertainty when designing climate mitigation policies? To what extent is the proposed policy mechanism realistically implementable, and does it meet the real constraints of policymakers and requirements of Sustainable Development Goals? Which measures can reduce demand-side CO_2 emissions and under what conditions?

Different disciplines have provided essential pieces of this big jigsaw puzzle, but much remains to be done. There is a big gap between what the current assessment tools can do and what social science highlights as pro-environmental behaviour in climate change mitigation movements. Social scientists and behavioural economists focus on the emotional and cognitive biases in the decision-making process. Namely, psychology theories predict motivation for individual energy behaviour change; behavioural studies demonstrate individual responses to the energy choices that depart from the 'perfect rationality' expected of homo economicus (Ebeling and Lotz, 2015; IPCC, 2014a); social studies emphasise the role of socio-demographics, culture, habits and structural aspects of individual energy consumption; while economics elaborate on how, under rational decision-making, carbon pricing and other fiscal instruments can trigger a change in energy consumption and demand.

In fact, policy instruments can activate demand-side solutions when they merge with the socio-economic context. The current climate change mitigation assessment tools need a truly interdisciplinary effort to address the posed questions.

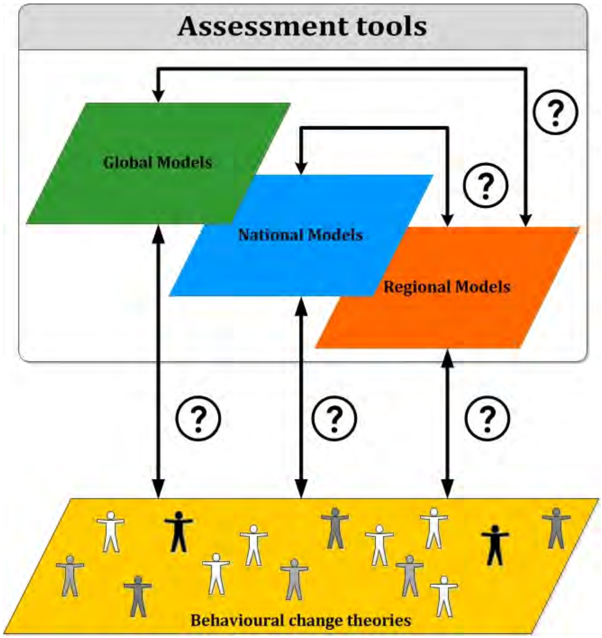


***Figure 1.1**: Scientific challenge*

1.3. Proposed approach

Agent-based computational modelling is considered the most promising approach to address the complexity of actors' decisions in climate–energy–economy models (Ebeling and Lotz, 2015; Gotts and Polhill, 2017; Rai and Henry, 2016; Stern, 2016; Stern et al., 2016a). Concerning the demand side and behavioural changes in energy consumption, this method is a frontrunner as it is designed to account for different lifestyles, bounded rationality and social influences (Abrahamse and Steg, 2009; Bamberg et al., 2007; Onwezen et al., 2013; Steg, 2016). A synthesis of social science and energy research – combining contributions from economics, psychology, sociology, governance and policy, technological innovation, statistics, and energy modelling – can provide a broad perspective to improve the assessment tools.

1.3.1. Empirical agent-based modelling

Agent-based modelling (ABM) is a contemporary approach and powerful tool for representing complex systems, where heterogeneous and adaptive agents interact spatially (Brown and Robinson, 2006; Farmer and Foley, 2009; Filatova et al., 2013; Hong and Page, 2004; LeBaron and Tesfatsion, 2008; Nyborg et al., 2016; Tesfatsion, 2006). Unlike other approaches, ABM is not limited to studies of perfectly rational agents or to abstract micro details in aggregate system-level equations. Instead, ABM can represent the behaviours – such as individual energy behaviours – using a range of behavioural theories. In addition, ABM provides functionality to examine how interactions of heterogeneous agents at the micro level give rise to the emergence of macro outcomes, including those relevant for climate mitigation such as adoption of low-carbon behavioural strategies and technologies over space and time (Rai and Henry, 2016). The ABM approach simulates complex and nonlinear behaviour that is intractable in equilibrium models.

Heterogeneity

Heterogeneity is an essential component of ABM; however, its range may vary. Individuals may differentiate from each other based on their socio-economic characteristics – e.g., income, education, and age – and their dwelling characteristics – e.g., type and size of their residence. In contrast to traditional economic models that may, for example, differentiate households into five representative income groups, economic climate change ABM usually draws economic and demographic parameters of its agents directly from empirical distributions (Berger and Schreinemachers, 2006; Brown and Robinson, 2006; Grimm et al., 2006). Therefore, differences in individuals' characteristics potentially lead them to different behaviours.

Bounded rationality

ABM is well suited to simulate boundedly rational behaviour (Gilbert, 2008; Rai and Henry, 2016; Stern, 2013). The concept of 'decision' bridges the distance between perfect rationality and behaviourally rich choices. A decision is a process through which the selection of one among numerous possible behaviour alternatives is performed (Barros, 2010; Simon et al., 1997). Individuals are often bounded by their own previous experiences and their cognitive abilities (personal aspect), the influence of others (social aspect), and information availability. Depending on the context, there are several ways to model bounded rationality (Filatova and Niamir, 2018).

Interactions and learning

Theory on innovation diffusion describes how a number of connected people adopting a new behaviour can spread a norm change through a social network. A group benefits from a certain individual's action, but no individual has sufficient incentive to act alone (Nyborg et al., 2016; Rogers, 2003). In modelling system dynamics, interactions and learning are the core (Bao and Fritchman, 2018), which is unique to ABM. Individuals in ABM can modify future choices by learning from their own experience and through their interactions with the environment and other individuals. For instance, while in economics learning is based on how expectations about future prices are formed and updated through interactions within the market institution (Hunt and Evans, 2009; LeBaron, 2006), in an environmental and climate change context, AMB could be implemented as rule-based learning (Axtell and Guerrero, forthcoming 2018; Gerst et al., 2013; Gotts and Polhill, 2009; Polhill and Gotts, 2009; van Duinen et al., 2016).

Out-of-equilibrium dynamics

Equilibrium assumes a relatively stable economic state. For example, fluctuations in the supply of and demand for energy instigate changes in energy prices. As economic theory posits, the supply and demand over time will converge to a steady state, and hence the price of energy will be relatively stable. However, standard neoclassical economics investigate situations when individual actions or expectations are in equilibrium with the outcome or aggregated behaviours. ABM goes further and enables us to discover how the economy behaves out of equilibrium when it is not in a steady state (Arthur, 2006; Tesfatsion, 2014).

To conclude, ABM is a simulation approach used 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 ABM to accommodate the complexity of human behaviour in energy systems (Gilbert, 2010; Rai and Henry, 2016; Stern, 2016).

This method is actively used in energy applications to study national climate mitigation strategies (Gerst et al., 2013; Gotts and Polhill, 2017), energy producer behaviour (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), the role of behaviour-changing feedback devices on energy demand (Jensen, 2017; Jensen et al., 2016), and changes in energy policy processes (Iychettira et al., 2017). Yet, in many cases, ABM still either lacks a theoretical framework (Groeneveld et al., 2017) or relevance to empirical data, especially when studying energy behaviour of households (Amouroux et al., 2013; Chappin et al., 2007).

1.3.2. Upscaling individual behaviour change

While ABM is a perfect tool to accommodate various theories and data, including qualitative behavioural data, it is usually used at rather small scales. Since ABM permits experimentation with numerous "what if" scenarios, it is essential to understand how model output data match empirical patterns and under what conditions. Even when the results fail to match empirical patterns, we can learn about the limits of our assumptions (Kwakkel and Jaxa-Rozen, 2016; Kwakkel and Pruyt, 2013; Premo, 2006). However, for integrated assessment model analyses, it is crucial to explore an extensive set of trajectories consistent with achieving the 1.5 °C target at national, regional or global scales. Moreover, models should account for uncertainties around the economy and technologies. Hence, advancing ABM to national and global scales implies not only increasing the number of agents – from thousands to millions or billions – but also modelling of economy-wide processes that go beyond individual behavioural change (Verburg et al., 2016).

Different methods of scaling up need to be explored, ranging from developing full-scale macroeconomic models from the bottom up (Fagiolo and Roventini, 2017) to the integration of ABM with complementary macro models (Krook-Riekkola et al., 2017; Niamir and Filatova, 2015; Niamir et al., 2018c; Safarzyńska et al., 2013; Smajgl et al., 2009). Yet, scaling up the various behavioural factors and strategies into larger populations of agents is still a challenge.

1.4. Research questions

This Ph.D. research aims at exploring the contribution of individual behaviour changes in mitigating climate change. To address this scientific challenge, one needs to have solid theoretical and empirical understanding of what constitutes behavioural changes in energy, and develop tools to aggregate these insights to quantitatively assess regional and national impacts of individual choices (Figure 1.2). In line with this research objective, four research questions are designed.

1. What are the main factors influencing individual energy behavioural changes in the transition to a low-carbon economy?
2. To what extent does heterogeneity in households' attributes, social interactions, and learning impact regional energy demand over time?
3. What are the macroeconomic impacts of individuals' behavioural changes on carbon emissions?
4. What is a systematic way of upscaling behavioural aspects of individual decision-making to assess macroeconomic impacts for climate change mitigation over time and space?

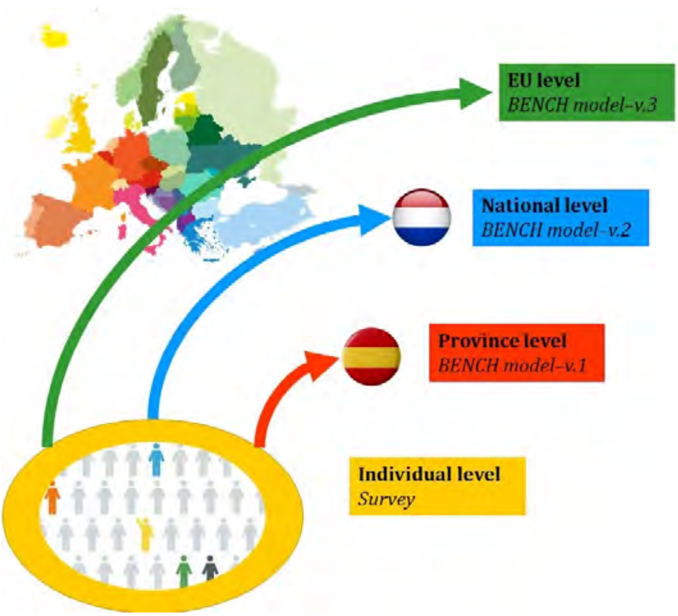


***Figure 1.2**: Research approach*

1.5. Outline of the dissertation

The dissertation consists of six chapters. Apart from the General Introduction and the Synthesis, there are four research chapters that systematically address the primary goal of the thesis step by step (Figure 1.3). Each chapter deals with one or two specific research question(s): *Chapter 1*, the General Introduction, gives an overview of the background and research questions and the scientific challenge of the dissertation. *Chapter 2* introduces the main determinants of individuals' energy behavioural change by analysing our households' survey data. *Chapter 3* shows the cumulative impacts of individual energy behaviour change by introducing the *BENCH-v.1* model. *Chapter 4* assesses the macroeconomic impact of individuals' energy behaviour change on carbon emissions (*BENCH-v.2* model). *Chapter 5* gives a solution to upscaling individual energy behaviour for climate change mitigation strategies. *Chapter 6*, the Synthesis, summarises and discusses the main findings and outlines perspectives for future research.

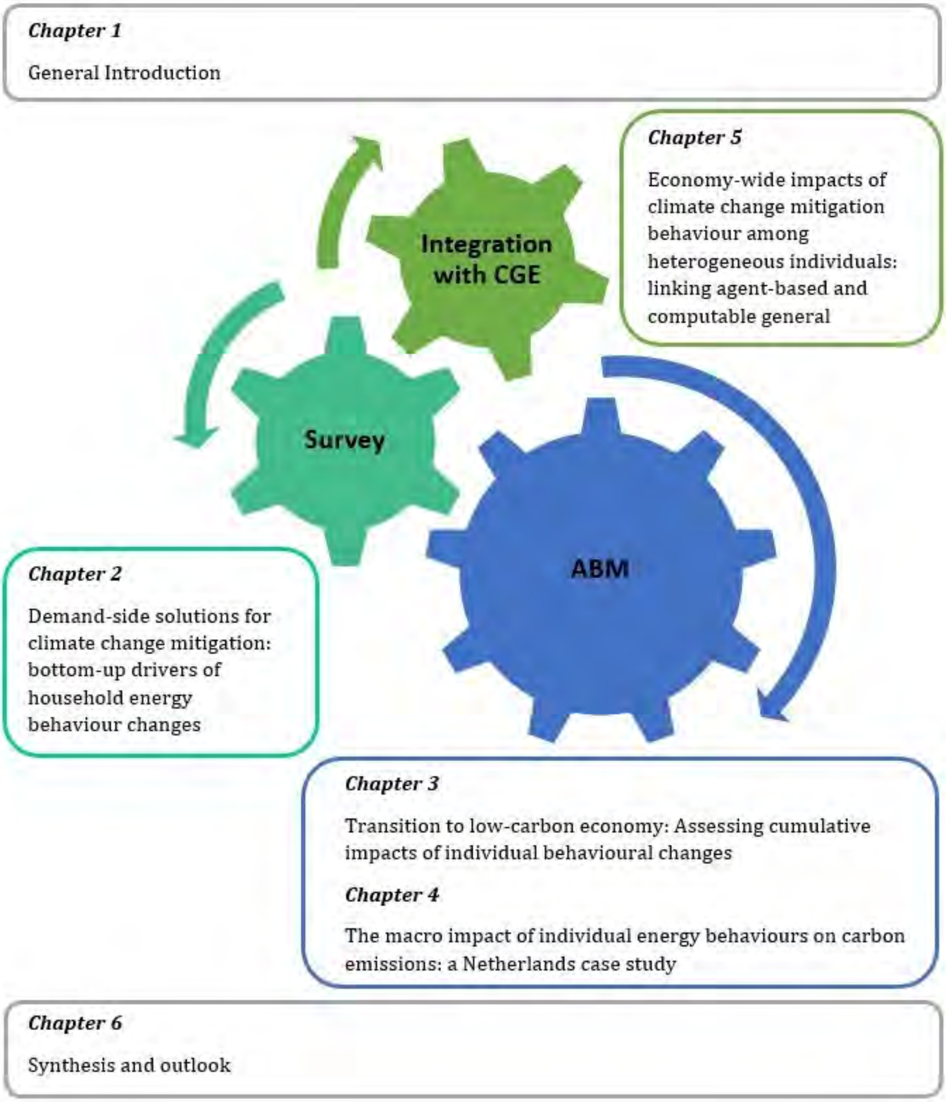


Figure 1.3: *Outline of the dissertation*

Chapter 2:

DEMAND-SIDE SOLUTIONS FOR CLIMATE CHANGE MITIGATION: BOTTOM-UP DRIVERS OF HOUSEHOLD ENERGY BEHAVIOUR CHANGE

Niamir, L., Ivanova, O., Filatova, T., Voinov, A. & Bressers, H.

Applied Energy (Under review)

Parts of this chapter also appeared in:

- Niamir, L., et al. (2018). *Impact of households' behavioural change on the energy demand in a transition to low-carbon economy*. IAEE International Conference, 10-13 June, Groningen-The Netherlands.
- Niamir, L., et al. (2017). *Household Energy Use and Behaviour Change Tracking Framework: From Data to Simulation.* Conference on Complex Systems, 17-22 September, Cancun-Mexico.
- EU FP7 COMPLEX Report D5.5.

Abstract

Households are responsible for 70% of CO_2 emissions and are important agents of change in any climate change mitigation strategy. While individual behaviour increasingly becomes a crucial element in energy transitions, bottom-up mechanisms facilitating them are not fully understood. To build a scientific understanding of individual energy use, we need to elicit how individuals choose to change their energy behaviour and which factors trigger or inhibit these decisions. This article explores individual energy consumption practices and behavioural aspects that may influence them. We quantitatively study the determinants of the three main energy actions: (1) *investments* in house insulation, installation of solar panels, and energy-efficient appliances, (2) *conservation* of energy by changing energy-use habits (e.g., switching off unnecessary devices, turning down the heat, and using less energy), and (3) *switching* between energy suppliers (switching to a green supplier, to another green supplier or to another conventional supplier). To address this goal, we designed and conducted a comprehensive survey among households (N= 1,790) in two EU regions: Overijssel, the Netherlands and Navarre, Spain. We quantitatively estimate how behavioural factors in combination with socioeconomic characteristics of households and structural attributes of dwellings may trigger or inhibit the three types of decisions by employing probit regression model and analysis. Our analysis demonstrates that awareness and personal and social norms are equally as important as monetary factors when it comes to individual energy actions. Education and structural dwelling factors appear to be very significant in bottom-up actions contributing to the reduction of the regional CO_2 footprint from the residential sector. These results have implications for governmental regulations and policies aimed at facilitating demand-side solutions in a transition to a low-carbon economy.

2.1. Introduction

Keeping greenhouse gas emissions below critical levels defined by the Paris Agreement is essential for effective climate change mitigation. These mitigation efforts vary from using renewable energy sources and new energy-efficient technologies to changing management practices and consumer behaviour. Significant attention is devoted to new energy technologies on both production and consumption sides. However, changes in individual behaviour and management practices as part of the mitigation strategy are often neglected (Creutzig et al., 2018a). Households are responsible for approximately 70% of global CO_2 emissions (Hertwich and Peters, 2009). Yet, despite behavioural change being emphasized as a crucial component of mitigation strategies worldwide (Creutzig et al., 2016; Creutzig et al., 2018a; IPCC, 2014a), empirical studies on individual energy-related choices and behavioural factors impacting them are scarce. In particular, while there are surveys exploring the adoption of energy technologies (Ameli and Brandt, 2015; Kobus et al., 2015; Li et al., 2017; Mills and Schleich, 2012; Mills and Schleich, 2009; Rai and Henry, 2016; Stern et al., 2016a) and examining pro-environmental personal and social norms (Bamberg et al., 2007; Steg and Vlek, 2009; Vassileva et al., 2013), they are rarely considered in combination. Moreover, behavioural factors and energy-technology choices are usually reported in an aggregated format, ignoring the fact that various socioeconomic groups may exhibit different behavioural traits. This research contributes to the scholarly literature on the role of behavioural changes in the transition to a low-carbon economy. The increasing scholarly understanding of the bottom-up factors behind the demand-side potential for climate mitigation, could guide effective policy development and implementation that differentiates between various household groups and actions.

The essential role of household socioeconomic characteristics on energy-efficient investments (e.g., technology adoption) is acknowledged in several studies. For example, a positive correlation has been shown between income and the probability of investing in energy-efficient technologies (Ameli and Brandt, 2015; Li et al., 2017; Long et al., 2018; Mills and Schleich, 2009; Sardianou and Genoudi, 2013; Vassileva et al., 2013). Some studies report that individuals with a higher level of education are more likely to adopt energy-efficient technologies (Michelsen and Madlener, 2012; Mills and Schleich, 2010, 2012; Sardianou and Genoudi, 2013). The evidence regarding the impact of age is mixed: some studies suggest that there is a negative correlation (Li et al., 2017; Mahapatra and Gustavsson, 2008; Michelsen and Madlener, 2012; Mills and Schleich, 2010, 2012; Mills and Schleich, 2009), other studies report that middle-aged people are more active in this regard compared to youngsters (Sardianou and Genoudi, 2013). Notably, these behavioural patterns may differ per type of investment (Ameli and Brandt, 2015). Other studies highlight the importance of dwelling characteristics for individual choices. The tenure status of the residence (owned or rented) affect a likelihood of investments in energy-efficiency in buildings. In particular, owners are more likely to invest in insulation and energy-efficient appliances than renters (Ameli and Brandt, 2015; Davis, 2010; Gillingham et al., 2012). Other dwelling characteristics – such as type (e.g. detached-house, apartment), size, location (e.g. rural, urban), and age of dwellings – appear to be important drivers of households energy-efficient investments (Ameli and Brandt, 2015; Hamilton et al., 2013; Michelsen and Madlener, 2012; Mills and Schleich, 2009; Wilson et al., 2018). Among behavioural factors, the literature brings attention to the importance of households' awareness and personal interest for energy decisions (Hutchinson et al., 2006; Kobus et al., 2015; Matsui et al., 2014; Vassileva et al., 2013). The role of local communities and social movements in individual energy decisions is acknowledged in several studies (Ghorbani and Bravo, 2016; Ostrom, 2006, 2007).

This article contributes to this discourse by reporting the results of an original large-scale survey (N=1,790) in two EU countries. We report unique data on behavioural and socio-demographic factors of households and their dwelling characteristics, and offer a quantitative analysis of the main drivers and barriers related to household changes in energy-use behaviour. The key theories in psychology provide a solid ground for identifying potential behavioural factors that are relevant for an energy behaviour change. The goal is to quantify which factors – socioeconomic (e.g., income, age), behavioural (e.g., personal and social norms, knowledge and awareness about the environment, social influence) and structural (e.g., size and type of house) – trigger or attenuate a transition to a lower and greener energy footprint at the household level. The innovative contribution of this paper is threefold:

(i) ***Empirical testing of theoretical concepts***: relying on theories of individual decision making from psychology, it develops a conceptual framework that integrates a variety of behavioural factors potentially relevant for studying energy behaviour changes. The role of various behavioural factors is quantitatively studied using original survey data;

(ii) ***Heterogeneity***: our analysis goes beyond the current empirical literature on individual energy behaviour by focusing on detailed actions within the three main types of households' choices: investment, conservation, and switching among providers. Within these three sets, we examine nine different actions and their dependence on both socioeconomic and behavioural characteristics of households as well as on structural dwelling factors. Hence, our quantitative assessment zooms beyond aggregates, acknowledging the fact that various socioeconomic groups may exhibit different behavioural traits for different actions;

(iii) ***Comparative analysis***: the two countries in our sample permit us to compare households' choices and the role of behavioural factors across contexts. On the one hand, it allows testing whether behavioural factors included in the theoretical framework matter in different cases, strengthening the validity of the proposed theoretical framework. On the other hand, a comparison across countries accounts for institutional, cultural and climatic factors that do affect households' choices but are often difficult to capture explicitly.

This research contributes to the scholarly literature on the role of behavioural changes in the transition to a low-carbon economy. The increasing scholarly understanding of the bottom-up factors behind the demand-side potential for climate mitigation, could guide effective policy development and implementation that differentiates between various household groups and actions. The paper proceeds as follows. The framework underpinning the survey is grounded in psychological theories aimed at understanding individual decision-making (Section 2.2). Section 2.3 reports the survey design in the two EU cases. The empirical correlation analysis is complemented by the probit regression model to estimate the main determinants of household energy behavioural change (Section 2.4). Section 2.5 discusses wider policy implications of this study.

2.2. Theoretical framework

Individual behaviour change is a multi-stage process. In application to environmental- and energy-related choices, three behavioural change theories are commonly applied: theory of planned behaviour (TPB), norm activation theory (NAT), and value–belief–norm (VBN) theory. TPB, formulated by Ajzen (1980a) and based on the theory of reasoned action, is one of the most influential theories in social and health psychology and has been used in many environmental studies (Armitage and Conner, 2001; Onwezen et al., 2013). TPB assumes that an intention to change behaviour is shaped by three main factors: human attitude toward a specific behaviour, subjective norms, and perceived behavioural control. NAT, originally developed by Schwartz (1977), operates in the context of altruistic and environmentally friendly behaviour. It is mostly focused on anticipating pride in doing the "right" thing and on studying the evolution of feelings of guilt. VBN theory (Stern, 2000; Stern et al., 1999) explains environmental behaviour and "good intentions" such as willingness to change behaviour (Nordlund and Garvill, 2003; Steg and Vlek, 2009; Stern et al., 1999), environmental citizenship (Stern et al., 1999), and policy acceptability (De Groot and Steg, 2009; Steg et al., 2005). In summary, TPB is focused on gain goal-frames, while NAT and VBN theory focus on normative goal-frames (Steg and Vlek, 2009). Some behavioural factors are common across these alternative conceptualizations of individual pro-environmental choices. While some empirical studies aim to test which of the theories explain choices better, others attempt to combine these theories to offer a more holistic view on individual decision-making (Ameli and Brandt, 2015; Bamberg et al., 2015). We follow the latter approach and introduce a framework that combines the strengths of the three key theories.

Figure 2.1 illustrates our conceptual framework that represents household energy behavioural change as a dynamic process unfolding in stages. Knowledge and awareness can have an important role in triggering individual behaviour change (Bamberg and Moser, 2007; Desa et al., 2011; Kobus et al., 2015; Matsui et al., 2014; Niamir and Filatova, 2016; Niamir et al., 2018b; Vassileva et al., 2013; Wilson et al., 2018). If individuals have enough knowledge and awareness about climate, environment and energy issues, a feeling of guilt develops and activates motivational factors, which may lead to energy-related behaviour change. Motivation is enhanced by personal and social norms (Abrahamse and Steg, 2009; Bamberg et al., 2007), which can lead to a feeling of responsibility and provoke an individual to change their behaviour. When intentions for the latter are high, individuals do a formal feasibility assessment according their income, dwelling conditions and own perceived behavioural control. Individuals compare their current energy-use habits with alternatives, and if things can be improved, the intention to pursue an alternative rises and may lead to a behaviour change. This conceptual framework combines some behavioural constructs that are common between TPB (in red) and NAT (in blue).

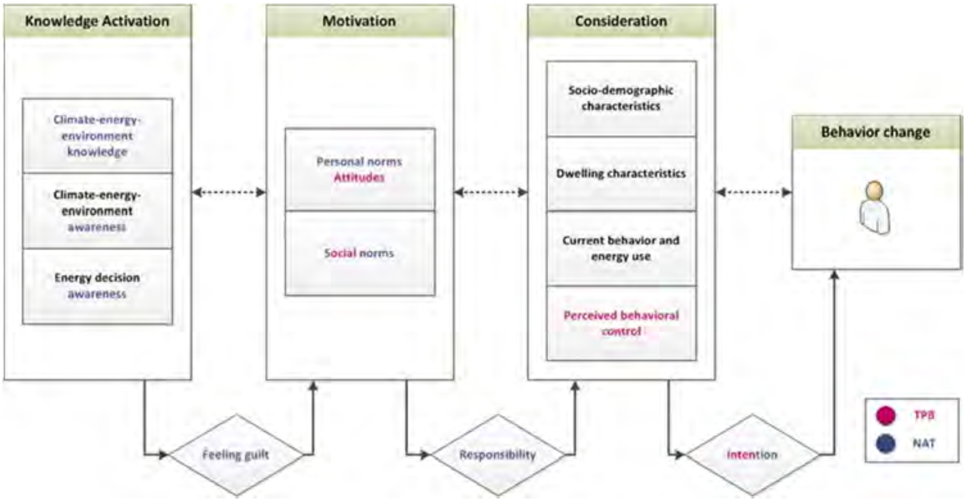


Figure 2.1*: Conceptual representation of multi-stage household behavioural change*

2.3. Methodology

Following the theoretical framework (Figure 1), we developed a survey to quantify behavioural changes regarding energy use. We designed a household survey to capture drivers and barriers in a decision-making process regarding the three types of energy-related actions: investment, conservation, and switching providers. For example, an individual could: (I) invest in green energy technology (e.g., solar panels or improved insulation); (C) pursue conservation behaviour by changing his or her own energy-use habits (e.g., switching off unnecessary lights, or running the washing machine at a full load); or (S) switch from grey to green energy providers.

2.3.1. Questionnaire design

Our questionnaire contains five sections consisting of 55 main questions about sociodemographic characteristic (10), dwelling characteristics (6), energy consumption, behaviour and sources (20), personal attitudes and opinion (7), and social networks (12). The questions are designed in different formats based on the type and nature of information required (Appendix A): multiple choice (e.g. education level, dwelling type, source of energy), Likert-type scale and semantic differential (e.g. all behavioural factors), Dichotomous and open-ended question (e.g. energy consumption and behaviour, social network). The questionnaire was also translated into Dutch and Spanish, in order to respondents have a freedom to choose their own preferable language among three languages (EN/NL/ES).

2.3.2. Survey and responses

We conducted the survey in two provinces in Europe that differ in terms of climate, culture, GDP, technology innovation and diffusion, renewable energy sources, institutional rules, and policies. In summer 2016, 1,035 households in the Overijssel province, the Netherlands, and 755 households in the Navarre province, Spain, completed our online questionnaire (Figure 2.2).

***Figure 2.2**: Survey case studies: the Overijssel province in the Netherlands and the Navarre province in Spain*

While interpreting any survey results (Section 2.4.1), the possibility of a response bias should be considered. The wording of questions and response scales (Ameli and Brandt, 2015), as well as the respondents' tendency to answer questions untruthfully, particularity for behavioural factors when they may feel pressure to give socially acceptable answers (Donaldson and Grant-Vallone (2002), can all contribute to a response bias. To minimize the chance of response bias, our survey took a 3-fold approach by assuring cross-questions, validation by an interdisciplinary team of experts (e.g., psychologist, energy economist, sociologist, governance and policy expert, statistician) and conducting pilot studies. In particular, to improve the survey quality and feasibility, we performed three pilot studies with: (a) a team of international experts (19 colleagues in the Netherlands and Spain); (b) a small sample of households in Overijssel; (c) a small sample of households in Navarre. The feedback from these pilots was integrated in the final questionnaire to increase its quality and the comprehension of questions by various participants. The final version of questionnaire was used for the large scale survey and distributed using the survey infrastructure of Kantar TNS[*] in summer 2016. An online multi-language, user-friendly, intelligent and interactive platform was provided (Appendix A). 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. We received back 1,790 valid completed questionnaires.

2.4. Results and discussion

In addition to presenting the survey descriptive analysis (Section 4.1), we perform the correlation and probit regression analysis of the survey data to examine the drivers and barriers related to household behavioural change toward a low-carbon economy. Firstly, we check the correlations between the behavioural factors (latent variables) to assess the validity of different items in our theoretical framework and to quantitatively assess the strength of these factors in a decision process (Section 2.4.2). Secondly, we employ the probit regression analysis to estimate the link between individual household attributes (socioeconomic and behavioural factors) and the likelihood of choosing one of the energy-related actions that contribute to climate change mitigation (Section 2.4.3).

2.4.1. Descriptive analysis

Table 2.1 provides descriptive statistics of the respondents in the two case-study provinces. Corresponding summary statistics on the socio-

[*] http://www.tnsglobal.com/

demographic characteristics of the population in the two provinces are also provided.

***Table 2.1**: Socioeconomic distribution in the region and within the survey sample: Navarre, Spain; Overijssel, the Netherlands Source: Eurostat, 2016 and own survey, 2016*

Factors		**Navarre, Spain**		**Overijssel, the Netherlands**	
		Regional	Survey sample	Regional	Survey sample
Population		637,486	755	1,134,465	1,035
Male population (in percentage)		49%	43%	49.9%	53.6%
Average income (thousand Euro per year)		18	Majority in income group 2 (10-30)	21	Majority in income groups 2 and 3 (10-50)
Education levels (in percentage)	ED 0-2	27.9%	16.4%	34.3%	47.8%
	ED 3-4	23.2%	22.8%	41.5%	26.6%
	ED 5-8	48.8%	60.8%	24.1%	25.6%

Tables 2.2 and 2.3 provide a brief overview of the descriptive statistics of the respondents, which represent the target population well. This information illustrates the distribution of socio-demographic and dwelling characteristics.

***Table 2.2**: Socio-demographic characteristic of surveyed households. Source: own survey, 2016*

Socio-demographic items	Overijssel	Navarre
Gender *		
female	46.4	57.1
male	53.6	42.9
Age **	53	41
Education *		
primary (ISCED 0-1)	3.0	2.0
secondary (ISCED 2-3)	49.6	14.4
tertiary (ISCED 4-5)	21.6	22.8
bachelor (ISCED 6)	14.6	26.6
master (ISCED 7)	9.6	30.5
doctorate (ISCED 8)	1.5	3.7
Employment status *		
employee (full-time, part-time)	49.9	57.8
self-employed	5.8	9.4
unemployed	5.5	14.2
homemaker (housewife/husband)	6.4	3.2
retired	23.6	5.6
student	2.1	9.1
other	6.6	0.5
Household annual income *		
less than 10 thousand euro	5.5	11.4
10-30 thousand euro	34.7	46.8
31-50 thousand euro	38.0	27.8
51-70 thousand euro	13.5	8.7
71-90 thousand euro	5.7	3.0
91-110 thousand euro	1.0	0.9
More than 120 thousand euro	1.6	1.3
Level of economic comfort *		
very difficult to live	7.1	10.2
difficult to live	15.1	20.9
coping	42.3	48.6
living comfortably	29.1	16.2
living very comfortably	6.3	4.2

* distribution is reported in percent **reported as mean

***Table 2.3**: Dwelling characteristics in survey sample. Source: own survey, 2016*

Dwelling characteristics items	Overijssel	Navarre
Type of residence [a]		
An apartment	14.9	77.8
A house	85.1	22.2
Tenure status [a]		
Own the residence	71	80.3
Rent the residence	29	19.7
Size of the residence [a]		
Less than 50 m²	4.5	3.3
50 m² - 100 m²	35.7	62.0
101 m² - 150 m²	35.7	22.4
151 m² - 200 m²	15.2	6.5
More than 200 m²	8.9	5.8
Age of the residence [a]		
Less than 5 years	4.4	7.2
5 to 10 years	7.4	22.0
11 to 20 years	15.8	26.4
21 to 35 years	26.1	20.9
36 to 50 years	25.4	14.8
More than 50 years	20.8	8.7
Energy label [a]		
A	15.7	11.7
B	15.9	11.7
C	11.7	7.8
D	4.6	3.7
E	4.6	3.1
F	4.0	1.6
Don't know	43.5	60.3

[*] distribution is reported in percent

Table 2.2 shows that our sample is sufficiently gender balanced in both case studies. Respondents in Navarre have a higher education level than in Overijssel, with the majority holding bachelor's or master's degrees. Regarding employment status, the majority of respondents in both cases are employed, followed by retired in Overijssel and unemployed in Navarre. More than half of the respondents in both provinces earn 10–50 thousand euros per year income. Nevertheless, there are more households with an income below 30 thousand euros in the Navarre case. This result may explain why the level of economic comfort in Overijssel is higher compared to Navarre.

The majority of respondents surveyed in Overijssel (85%) live in houses, while 78% of the Navarre respondents live in apartments. Most respondents in both provinces own the place in which they live. The housing stock is generally older in Overijssel than in Navarre. In both case studies, the majority of households were not aware of the energy rating of their residence (Table 2.3).

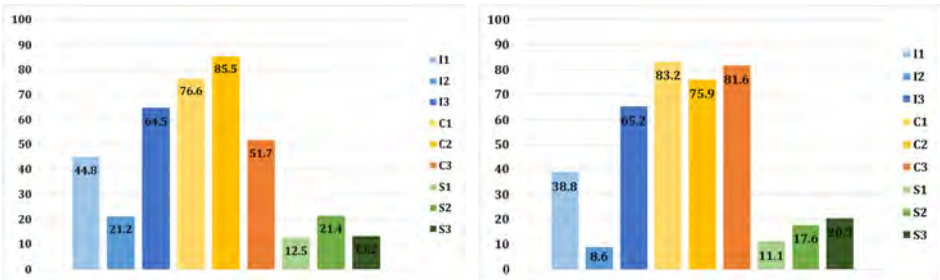
Table 2.4 reports summary statistics on behavioural factors that could affect energy decisions of households. All behavioural factors are measured on a Likert scale of 1–7 (see Appendix A). It illustrates that knowledge and personal norms play the most important role in deciding whether to make any changes in a household-level energy use in both countries. Social norms and perceived behavioural control, which is often associated with financial factors among others, are more important for Spanish respondents compared to the Dutch.

Table 2.4*: Importance of* behavioural *factors among survey respondents, on a scale from 1-7. Source: own survey, 2016*

Behavioural items		**Overijssel**	**Navarre**
Knowledge	Climate-Energy-Economy Knowledge (CEEK)	4.2 (0.7)	5.0 (0.8)
	Climate-Energy-Economy Awareness (CEEA)	4.9 (0.8)	5.4 (0.8)
	Energy Decision Awareness (EDA)	4.5 (1.0)	5.3 (1.1)
Motivation	Personal Norms (PN)	4.6 (0.9)	5.4 (1.0)
	Social Norms (SN)	3.3 (1.1)	4.5 (1.2)

Consideration	Perceived Behaviour Control-investment (PBC1)	4.4 (1.1)	5.0
	Perceived Behaviour Control-Conservation (PBC2)	3.5 (1..4)	4.6 (1.4)
	Perceived Behaviour Control-Switching (PBC3)	3.4 (1.4)	5.0 (1.3)

Figure 2.3 shows the distribution of energy-related actions, which our survey respondents undertook in the last 10 years. Between 2006-2016 Dutch households were more active in big investments including house insulation (6% more on I1) and solar panels (12.6% more on I2), and in switching to green providers (1.4 – 3.8% more on S1,1) compared to the Spanish respondents. The latter appeared more willing to change habits – 6.6% more respondents in Navarre practice switching off unused devices (C1) and 30% more actively adjust daily household-appliances-use habits (C3) – compared to the Dutch.



(a): Overijssel, the Netherlands (b): Navarre, Spain

***Figure 2.3**:* Shares of survey respondents who undertook energy-related actions in the past 10 years (2006-2016), in %. Here the blue I-group refers to investments (I1 – in house insulation, I2 – in solar panels, I3 – in energy-efficient appliances); the orange C-group refers to conservation due to a change in habits (C1 – switching off unnecessary devices, C2 – moderate inside temperature regulation, C3 – adjusting daily habits such as running a full-load washing machine); the green S-group refers to switching (S1 – to green energy, S2 – switching to another green provider, S3 – to a conventional energy provider). Source: own survey, 2016.

2.4.2. Correlation analysis

Table 2.5 presents the correlation matrix for the five latent variables representing behavioural factors for the Overijssel (upper triangular matrix) and Navarre (lower triangular matrix) provinces separately. In both cases, all five latent variables correlate positively and substantively. While personal norms (PN) correlate strongly with knowledge (CEEK) and awareness (CEEA, EDA), social norms (SN) have weak positive relationships: the correlation of knowledge and awareness (CEEK, CEEA, EDA) with social norms (SN) is two to three times smaller compared to personal norms (PN). Knowledge and awareness are more tightly connected to social networks for Spanish respondents compared to the Dutch.

Table 2.5*: Correlation of latent constructs (knowledge activation and motivation) for Overijssel (N=1,035, upper triangular matrix- in yellow) and Navarre (N=755, lower triangular matrix- in grey). Source: own survey, 2016*

Variables	CEEK	CEEA	EDA	PN	SN
CEEK	–	0.64	0.49	0.45	0.16
CEEA	0.66	–	0.79	0.71	0.21
EDA	0.53	0.76	–	0.76	0.22
PN	0.52	0.77	0.88	–	0.37
SN	0.27	0.35	0.27	0.40	–

Note: CEEK=climate–energy–economy knowledge; CEEA=climate–energy–economy awareness; EDA=energy decision awareness; PN=personal norms; SN=social norms

2.4.3. Regression analysis: understanding households' likelihood to pursue individual level climate mitigation actions

We assume that households' decisions regarding energy use – investment (I), conservation (C), and switching (S) – are independent of each other and can occur simultaneously. Our survey differentiates between sub-actions within each category. A household may invest in house insulation (I1), install solar panels (I2) or buy energy-efficient appliances (I3). Alternatively, energy use improves by switching off unnecessary devices (C1), turning down the heater / air conditioner (C2) or using less energy by changing daily habits (C3) such as running a full-load washing machine. Lastly, a household may improve its energy footprint by switching to green energy (S1), or switching to another green (S2) or conventional (S3) energy provider. For each of the choices, we developed a statistical model of the household energy decision process based on the discrete "yes" or "no" decisions for the three actions (I, C, S) and their respective sub-actions using a probit regression model (Ameli and Brandt, 2015; Mills and Schleich, 2010). The expected utility of each of the sub-options is Modelled as follows:

$$y_{ij}^{*} = x_{ij}\beta_i + \varepsilon_{ij} \tag{1}$$

where y_{ij}^{*} is a latent variable that captures the utility of household j associated with its choice to implement sub-option i related to energy investment, energy conservation, or switching (I1–S3). x_{ij} is the vector of explanatory variables, including socioeconomic characteristics of the individuals, dwelling characteristics, energy-use patterns, financial and ownership situation, as well as indicators for personal and social norms. β_i is the parameter vector that needs to be estimated based on the survey data using maximum likelihood econometric methods, and finally, ε_{ij} is the vector of error terms. Individual choice utilities and, hence, preferences of households cannot be observed directly from the survey data and are modelled using the probit discrete choice model decision rule:

$$y_{ij} = 0 \ if \ y_{ij}^* < 0$$
$$y_{ij} = 1 \ if \ y_{ij}^* \geq 0 \tag{2}$$

This decision rule means that household j implements a particular sub-action, i (I1–S3), when its expected utility is non-negative, and the household does not implement a particular sub-option when its expected utility is strictly negative (Eq. 2).
Tables 2.6-8 present the results of the regression analysis using the probit model in STATA 14 for each of the sub-options and include the coefficient levels as well as their p-values. P-values associated with each of the regression parameters β_i indicate whether a particular variable is statistically significant, as well as the level of its statistical significance. We consider 1%, 5%, and 10% levels of significance in the interpretation of the probit regression results.

2.4.3.1. Factors affecting a probability of a household to invest

We also observe that the country variable (ES vs. NL) has a strong (99% confidence interval) influence on taking a decision to install solar panels. Dutch households are more active in installing PVs. Naturally, country-specific fiscal rules, climate change mitigation regulations, culture, and climate may act as drivers or barriers in our two case-study provinces.

Under socio-demographic factors, education has a positive and very significant impact on insulation and PV installation (I1, I2 in Table 2.6). The probability of taking these actions increases with the level of education (95% confidence interval). Higher economic comfort leads to more investments in appliances (I3, 95% confidence interval). Households are ready to make investments in energy-efficient appliances as soon as they can cope with their other expenses and live comfortably given their income. Also, we observe gender having a very significant (99% confidence interval) impact on installing solar panels (I2), with men being more likely to make this decision than women. Personal norms appear to be very significant in all three investment decisions and have a positive role: a higher level of personal norms leads to more investments (Table 2.6).

Regarding the characteristics of the residence, we observe that type (apartment vs. house), age, and size have impacts on households' big investment decisions (I1, I2). Type of residence is very significant (99% confidence interval): owners of houses are more eager to install solar panels and invest in insulation. Age of the residence has positive impacts (99% confidence interval) on the likelihood of being insulated. Older buildings tend to be insulated more often as compared to new buildings that already have high energy ratings. However, age has a negative impact (95% confidence interval) on the likelihood of installing solar panels, with more PVs installed on new buildings than on older ones. Size of residence has a positive and significant impact on large investments: owners of larger residences are more likely to invest in PVs or to insulate their houses. The fact that large houses are usually owned by people with higher incomes, and potentially have more energy leakage, makes insulation a priority for their owners among other energy-efficient decisions. Also, larger houses have larger rooftop areas to install PVs. We also found a meaningful correlation between the energy label of residence and investing in insulation (Table 2.6).

In general, the probability of households investing is highly correlated with residents' education level (95%), personal norms (90–99%), and type (99%) and size of their residence (90–95%). Hence, personal intentions, knowledge and awareness, and type and size of a house are core in promoting energy-efficient investments among households.

Table 2.6: *Probit regressions (PR.I) on investment decisions (I1–I3). Dependent variables: investments in insulation, PV installation, and energy-efficient appliances (N=1,790)*

Variables	**I1: Insulation**		**I2: PV installation**		**I3: Energy-efficient appliances**	
	coefficients	p-value	coefficients	p-value	coefficients	p-value
country	0.1397251	0.1340	−0.4265909	0.0000***	0.047433	0.6110
income	0.0149715	0.6430	−0.0298901	0.4530	−0.0226898	0.4890
gender	0.0795755	0.1980	0.2792288	0.0000***	0.004528	0.9420
education	0.0563284	0.0400**	0.0779388	0.0190**	0.0294806	0.2870
eco-comfort	0.0523404	0.2480	0.0021244	0.9690	0.1059369	0.0210**
age	0.0008106	0.0000***	0.001021	0.0000***	0.0001881	0.2360
tenure	−0.1028189	0.1670	0.0462172	0.6090	−0.0854744	0.2500
energy label	−0.0769971	0.0650*	−0.075806	0.1320	−0.0575989	0.1780
type	0.4265	0.0000***	0.5005143	0.0000***	0.0904679	0.3130
age of residence	0.0883428	0.0000***	−0.0577463	0.0440**	−0.031426	0.1810
size	0.0857047	0.0140**	0.1287344	0.0010***	0.0510185	0.1530
electricity	0.0000182	0.3820	−0.0000937	0.0000***	0.0000697	0.0010***
gas	0.0000488	0.0480**	0.0000127	0.6980	0.000008	0.7500
personal norms	0.052849	0.1000*	0.082771	0.0350**	0.095038	0.0030***
social norms	0.0020971	0.9330	0.003869	0.9000	−0.0161594	0.5160

Note: * refers to 10% significance level, ** refers to 5% significance level, and *** refers to 1% significance level

2.4.3.2. *Factors affecting a probability of a household to conserve energy*

Energy conservation actions (C1–C3) correlate significantly with the country dummy (Table 2.7). Specifically, Spanish households are more active in switching off unnecessary devices (C1, 99% confidence interval) and using less energy (C3, 99% confidence interval), while Dutch households are more likely to reduce their use of the heater / air conditioner (C2, 99% confidence interval).

Analysis of socio-demographic factors highlights the roles of gender and economic comfort. Gender bias is observed under C2 and C3 decisions: women pursue more energy conservation compared to men. Moreover, we detect that households not satisfied with their current economic situation are more likely to try to save money by reducing their energy bill and switching off unnecessary devices (economic comfort, 95% confidence interval). Personal norms appear very significant and positive (99% confidence interval) for all three conservation actions.

Type and energy label of residence emerge as important factors in conserving on heating/cooling (C2): people living in houses have an extra incentive to turn down the heating/cooling compared to people living in apartments. The worse the energy label, the higher the energy leakage and the more people try to conserve their energy use by reducing heating/cooling. Consequently, residences with low energy labels potentially have more energy leakage leading to growth in energy consumption and bills. To save energy and money, households either should invest in insulation (Table 6) or save energy by turning down the heating/cooling system and adapting to less comfortable temperatures.

In summary, the likelihood of households conserving energy (C1–C3) correlates with personal norms and the type, energy label, and age of their residences.

***Table 2.7**: Probit regression conservation (PR.II). Dependent variables: switching off devices when not in use, turning down the heater / air conditioner and generally using less energy (N=1,790)*

Variables	C1: Switch off or unplug devices when not in use		C2: Turn down the heater / air conditioner		C3: Use less energy	
	coefficients	p-value	coefficients	p-value	coefficients	p-value
country	0.2706158	0.0080***	−0.3943574	0.0000***	0.7156096	0.0000***
income	−0.0427815	0.2340	−0.0076126	0.8400	−0.0591228	0.0800*
gender	−0.0125411	0.8560	−0.1723292	0.0160**	−0.2067435	0.0010***
education	−0.0233181	0.4430	0.0272647	0.3920	0.0256838	0.3710
eco-comfort	0.1049109	0.0340**	−0.0567201	0.2740	−0.0145656	0.7560
age	0.0001355	0.4290	−0.0004648	0.0090***	0.0002276	0.1630
tenure	−0.0457255	0.5770	−0.1251689	0.1390	−0.0582215	0.4490
energy label	0.0587441	0.2060	0.0965134	0.0490**	0.0124117	0.7750
type	0.1060117	0.2780	0.3023552	0.0030***	0.0322179	0.7290
age of residence	−0.0009385	0.9710	−0.0716471	0.0070***	0.0019361	0.9370
size	0.0169433	0.6630	−0.0368238	0.3740	0.007845	0.8280
electricity	0.000021	0.3680	−0.0000	0.9130	0.0000149	0.4950
gas	−0.000005	0.8500	0.0000819	0.0060***	0.0000161	0.5540
personal norms	0.1134906	0.0010***	0.1534471	0.0000***	0.1619213	0.0000***
social norms	0.0108234	0.6950	−0.0547073	0.0590*	0.0261578	0.3130

Note: * refers to 10% significance level, ** refers to 5% significance level, and *** refers to 1% significance level

2.4.3.3. *Factors affecting a probability of a household to switch energy providers*

Switching to another green provider (S2) correlates significantly with the country dummy (Table 2.8, %99). This result could reflect greater market competition between providers in Netherlands.

Education plays an important role in the transition to green energies (S1, S2): households with higher levels of education are more likely to switch (95% confidence interval). In addition, this is the only place where we capture the correlation between income and household decisions (S3): lower income groups are more likely to switch to conventional providers. This result can be explained by these households seeking lower costs, which are still found with conventional energy providers. Personal norms appear significant (95% confidence interval) for switching to another green energy provider: households switching to greener energy have higher personal norms.

Regarding the residence characteristics, age and energy rating come out as important. Owners of older buildings are more likely to switch to another green provider (99% confidence interval). Residences with a lower energy label rating tend to switch to a green provider (95% confidence interval).

The decisions to switch to a green provider (S1) and from one green provider to another (S2) tend to have quite similar types of explanatory variables. However, in switching to another green provider, personal norms play an important role.

***Table 2.8**: Probit regression on switching (PR.III). Dependent variables: switching supplier – from grey to green, from green to another green, from grey to another conventional provider (N=1,790)*

Variables	S1: Switch to green energy		S2: Switch to another green energy provider		S3: Switch to another conventional provider	
	coefficients	p-value	coefficients	p-value	coefficients	p-value
country	−0.1739922	0.1430	−0.2817241	0.0070***	0.1780758	0.1020*
income	0.0379236	0.3540	−0.0410168	0.2680	−0.0634739	0.1070*
gender	0.0833157	0.2960	0.0357666	0.6080	0.0819696	0.2660
education	0.0856276	0.0130**	0.0639826	0.0380**	0.0266516	0.4050
eco-comfort	0.016136	0.7710	0.0036614	0.9430	−0.021244	0.6960
age	0.0010655	0.0000***	0.0006837	0.0000***	0.0005574	0.0030***
tenure	0.073537	0.4340	−0.0470855	0.5730	−0.026532	0.7630
energy label	−0.0974067	0.0730*	0.0245303	0.5980	0.0700238	0.1560
type	0.0618649	0.5900	0.0194978	0.8460	−0.0912484	0.3910
age of residence	0.0129401	0.6650	−0.0869868	0.0010***	−0.0172708	0.5280
size	0.0529026	0.2340	0.059853	0.1280	0.0601634	0.1510
electricity	−0.0000671	0.0140**	0.0000291	0.2200	0.0000	0.9820
gas	0.0000112	0.7320	−0.0000382	0.1850	0.0001035	0.0000***
personal norms	0.0648121	0.1180	0.080775	0.0290**	−0.0434834	0.2560
social norms	0.0450193	0.1620	0.0355918	0.2090	−0.0095217	0.7500

Note: * refers to 10% significance level, ** refers to 5% significance level, and *** refers to 1% significance level

2.4.4. Predicted probabilities

Under the probit discrete choice model, the probability of a household implementing a sub-option (I1–S3) is Modelled as follows:

$$P\left(y_{ij}=1 \middle| x_{ij}\right)=\frac{\exp\left(x_{ij}\,\beta_i\right)}{1+\exp\left(x_{ij}\,\beta_i\right)}=\Lambda\left(x_{ij}\,\beta_i\right) \tag{3}$$

where $\Lambda\,(x_{ij}\,\beta_i)$ denotes the logistic cumulative distribution function (Ameli and Brandt, 2015). To follow the socio-demographic, structural, and behavioural factors' magnitudes, we tested the marginal effect across a range of their values. Among all factors, personal norms and education demonstrated significant results. Also, the regression analysis (Sections 2.4.3.1–2.4.3.3) unanimously showed the importance of these two factors. Figure 4 illustrates the effect of personal norms and education levels on nine household behaviours (I1–3, C1–3, S1–3).

A higher level of personal norms increases the probability of energy investments (I1–3, blue lines), conservation (C1–3, orange lines), and switching to green providers (S1 and S2, green lines), in contrast to switching to another conventional supplier (S3, light green line). This result clearly shows that an increase in the level of personal norms leads to a large increase in the probabilities of transition to a low-carbon economy.

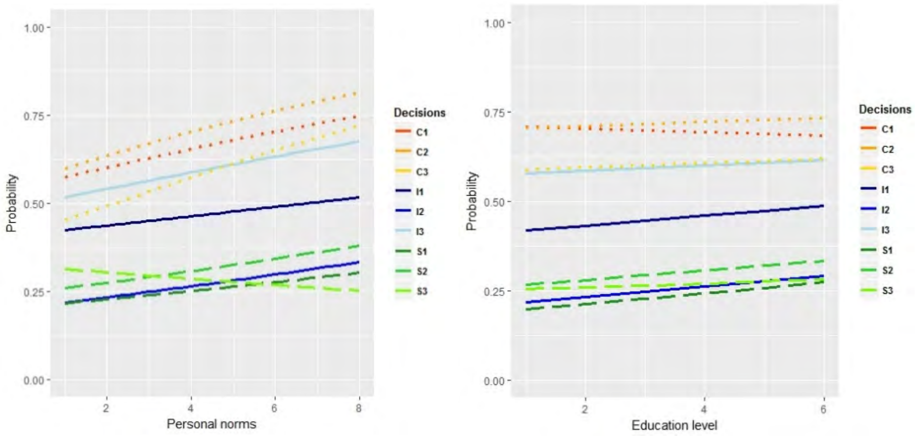


***Figure 2.4**: Predicted probability of energy-related actions (I1–S3) depending on personal norms and education level*

2.5. Conclusions and policy implications

This article offers the strong evidence of the importance of behavioural factors in making energy-related decisions and in promoting behavioural solutions for climate change mitigation in Europe. We develop a conceptual framework rooted in behavioural theories from psychology and designed a questionnaire based on it. By using our survey data we quantitatively investigate the relevance of behavioural factors in this framework (Section 2.4.2). Several behavioural factors (e.g., knowledge and awareness) influence personal norms: the higher the level of knowledge and awareness about environmental and climate issues, the higher the level of personal norms. The impact of the societal institutional rules – culture, fiscal rules, and regulations – on individuals is inevitable, as confirmed by the significant effect of the country dummy. Moreover, households are not making decisions in isolation: they are prone to the influence of interactions with peers in their social networks and local communities. In fact, social norms have an essential role in shaping personal norms. Together, personal and social norms can trigger individuals to make energy-efficient decisions.

We quantitatively assess nine different energy-related actions and their dependence not only on behavioural factors but also on socio-demographic and structural dwelling factors. Among dwelling characteristics, the type, size, and age of the residence have a strong influence on energy investments and conservation. As expected, people living in house are more eager to pursue large investments and have an extra incentive to save energy by turning down the heater / air conditioner. Analysis of socio-demographic factors highlights the role of education in household energy-related decisions, particularly in energy investments and in switching to green energy sources. Educated households are more active in improving their energy efficiency in both case studies. A higher level of education enables more insight, knowledge, and awareness of environment–climate–energy issues, which all consequently affect personal norms and lead to behaviour change. The comparative analysis between two countries allows us to validate the conceptual framework by testing the relation of behavioural factors across contexts (Section 2.4.2). The country dummy serves as a proxy to capture to what extent differences in institutional, cultural and climatic factors affect households' energy choices. Namely, our analysis shows that Dutch households are more active in investing in house insulation (I1) and in installing PVs (I2). However, Spanish households pioneer in energy conservation by changing daily habits (C1, C3). We also find that switching to another green provider (S2) correlates significantly with the country dummy which could reflect greater market competition between green providers in Netherlands.

To conclude, the empirical analysis clearly demonstrates that behavioural factors, next to structural factors and education, play at least as important a role in energy decisions – investment, conservation, and switching – as monetary factors such as income. This result has implications for the type of governmental regulations and policies that can be implemented to facilitate the green transition. In particular, policies such as the provision of targeted information and social advertisements for the broader public in combination with education to create more knowledge and awareness in the longer run could accompany and reinforce the effectiveness of other stimuli such as subsidies. Including special topics in educational programs can help to change the level of understanding, awareness, and individual norms of households. These so-called nudging or soft policy measures may prove more effective in promoting green energy solutions implemented by households compared to fiscal policy measures alone. A variety of policy instruments should be used with combinations of various financial, social, and other instruments in the policy mix complementing and reinforcing each other.

Appendix A

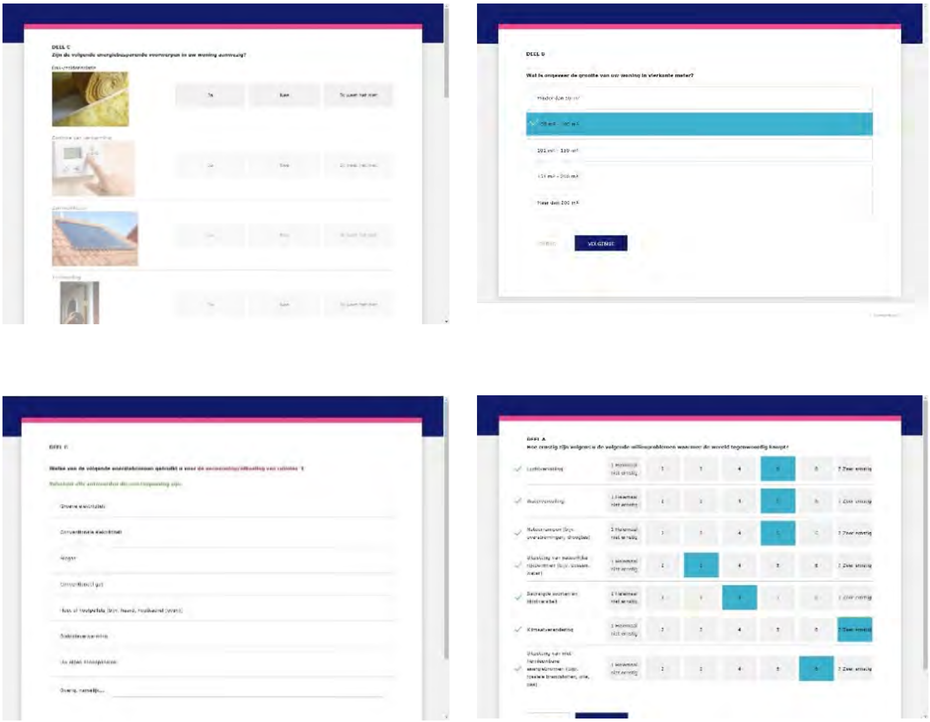


***Figure 2.A.1**: Questionnaire design, different type of questions. Source: own online survey, 2016*

Appendix B

***Table 2.B.1**: Items of psychological factors, "Knowledge". Source: own survey, 2016*

Knowledge
Climate-Energy-Economy Knowledge
Climate change is caused by a hole in the earth's atmosphere.
Climate change issues should be dealt with primarily by future generations.
Climate-Energy-Economy Awareness
I believe that ….
the effect of environmental issues on human health is worse than we realize.
environmental issues, even in one region, affect other regions.
environmental impacts are frequently overstated.
environmental issues like climate change is caused by fossil fuels use.
protecting the environment is a means of stimulating economic growth.
nature is fragile and if we don't take care of it properly, it could lose its balance.
Energy Decision Awareness
I believe that my energy source choice (renewables or fossil fuels) has an impact on the environment.
I think avoiding fossil fuels use will help solve wider environmental issues.

all items measured with Likert scales with labelled end-points (1 ="totally disagree" and 7="totally agree")

***Table 2.B.2**: Items of psychological factors, "Motivation". Source: own survey, 2016*

Motivation
Perceived Behavioural control *
I believe that ….
the effect of environmental issues on human health is worse than we realize.
I can help solve environmental, climate and energy problems.
when I use fossil fuels, there are greenhouse gases emitted which threaten human health.
every time we use coal, oil or gas, we contribute to climate change.
Reducing my energy consumption is a personal willingness and self-motivation
Social Norms **
I will reduce my energy consumption if …
more practical information on how to reduce energy consumption at home
funding out that my households uses more energy than similar households
public labels which neighbors can see
encouragement or actions of friends and family
encouragement or actions of group/associations that I am part of them
Governmental policies and subsidies (i.e. municipalities, provincial, national level)

** all items measured with Likert scales with labelled end-points (1 ="totally disagree" and 7="totally agree")*
*** all items measured with Likert scales with labelled end-points (1 ="not important" and 7="very important")*

***Table 2.B.3**: Items of psychological factors, "Consideration". Source: own survey, 2016.*

Consideration
Perceived Behaviour Control-investment (PBC1)
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 produce part of my green energy consumption (e.g. install solar panel or fund a wind turbine).
Perceived Behaviour Control-Conservation (PBC2)
I would reduce my energy consumption if energy prices would be higher.
I would reduce my energy consumption, if more practical information on how to reduce energy consumption at home would be available.
Perceived Behaviour Control-Switching (PBC3)
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.

all items measured with Likert scales with labelled end-points (1 ="totally disagree" and 7="totally agree")

Chapter 3:

TRANSITION TO LOW-CARBON ECONOMY: ASSESSING CUMULATIVE IMPACTS OF INDIVIDUAL BEHAVIOURAL CHANGES

Niamir, L., Filatova, T., Voinov, A. & Bressers, H.

Energy Policy 118 (2018) 325–345

Parts of this chapter also appeared in:

- Niamir, L., et al. (2017). *Transition to Low-carbon Economy: Simulating Nonlinearities in the Electricity Market, Navarre Region-Spain*. Advances in Social Simulation 2015, Springer.
- Niamir, L., et al. (2016). *Tracing Behavioural Change in Climate-Economy-Energy Systems: Agent-Based Energy Market and Computable General Equilibrium Model*. Advancing in Modelling and Integrated Assessment, COMPLEX, Vol.4.
- Niamir, L., et al. (2016). *From Climate Change Awareness to Energy Efficient Behaviour*. International Congress on Environmental Modelling and Software, 10-14 July, Toulouse-France.
- EU FP7 COMPLEX. Reports D5.6 and D5.7

Abstract

Changing residential energy demand can play an essential role in transitioning to a green economy. Environmental psychology suggests that behavioural changes regarding energy use are affected by knowledge, awareness, motivation and social learning. Data on various behavioural 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 behavioural changes among heterogeneous households. We focus on the representation of the multi-step changes in individual energy use behaviour and on a quantitative assessment of their aggregated impacts on the regional level. We understand the behavioural 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.

3.1. 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). To understand the role of individuals in a transition to low-carbon economy, calls for quantitative analysis of behavioural changes with respect to energy use.

Residential energy use accounts for almost 24% of GHG emissions in Europe. Early assessments indicate that behavioural 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 behavioural 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, behavioural shifts among households are often modelled 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 behavioural 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 behavioural 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 behaviour, and highlight the role of awareness, information and social peer influence on this process (Abrahamse and Steg, 2011; Frederiks et al., 2015). Omitting these behavioural 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.

Empirical data about various behavioural 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 Modelling (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 behaviour in energy systems (Rai and Henry, 2016). ABM departs from using system-level equations explicitly representing the behaviour 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 behaviour (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., 2016a). Yet, many ABMs still either lack a theoretical framework (Groeneveld et al., 2017) or relevance to empirical data, especially when studying energy-related behaviour of households (Amouroux et al., 2013; Chappin et al., 2007).

This paper aims to quantitatively explore the impact of behavioural 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 Modelling based on economic factors alone, by explicitly accounting for potential behavioural drivers and barriers in a formal model. Secondly, while acknowledging the importance of solid empirical behavioural data collected in harmony with recent findings in environmental psychology, the article introduces a simulation method that allows to aggregate individual behavioural 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 modelled energy market relying on theoretically and empirically-grounded agent rules. This combination of behavioural data collection via a survey with a simulation Modelling 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?

***Table 3.1**: Overview of energy-related behaviours in the housing sector*

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

The article proceeds as follows. By drawing on critical insights on behavioural change from environmental psychology, we illuminate the key factors of energy-related behaviour (Section 3.2) and present the design and summary of our survey (Section 3.3.1). We apply ABM to assess the cumulative impacts of individual behavioural changes with respect to energy use, accounting for socioeconomic heterogeneity, psychological factors and social network influence (Section 3.3.2). While grounding the model in these psychological and economic micro-foundations, we focus our analysis on the emerging macro properties (Section 3.4). 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 behavioural 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 3.5).

3.2. 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 behavioural changes (Table 3.1). 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 behavioural 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 behavioural 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)* and Theory of Planned Behaviour (TPB)†. They argue that the NAT variables such as awareness and personal norms significantly add to the explanation of energy-related behaviour, more than the TPB variables such as attitudes and perceived behaviour 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 behaviour. 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 behaviour change and decision making models in illustrating consumers energy behaviours by comparing TPB and the Value Belief Norm theory. He argues that using any theoretically based framework to understand human behaviour is inheritably linked to individual psychological variables – beliefs, norms and attitudes – which should be tested empirically. However, concrete studies of residential

---

* NAT is originally developed by Schwartz, S.H., (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 behavioural. The theory assumes that individual awareness and a responsibility one holds affect pro-environmental actions.

† TPB is formulated by Ajzen, I. (1980b) Understanding Events - Affect and the Construction of Social-Action - Heise,Dr. Contemporary Psychology 25, 775-776. based on the Theory Reasoned Action. It is one of the most influential theories in social and health psychology (Armitage, C.J., Conner, M. (2001) Efficacy of the theory of planned behaviour: A meta-analytic review. British Journal of Social Psychology 40, 471-499, 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. Journal of Economic Psychology 39, 141-153.). TPB assumes that an intention to act is determined by 3 main factors: human attitude toward specific behaviour (action), subjective norm, and perceived behavioural control.

energy-related behavioural changes, verified by detailed empirical data, are rare (Bhushan et al., 2016; Stern et al., 2016a).

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 3.2).

***Table 3.2**: Use of various decision-making theories to specify behavioural rules in environmental and energy ABM*

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

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 behaviour. Personal norms are at the core of this theory, and are used to explain individual behaviour. Personal norms are determined by two main factors: awareness and responsibility, while in turn they are influenced by subjective norms and perceived behaviour 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 behaviour. The awareness indicates knowledge that choosing (or not) a specific behaviour has certain consequences. The household feels responsibility for delivering a particular behaviour when they are sufficiently aware, and are motivated by their environment (Abrahamse and Steg, 2009; Onwezen et al., 2013; Schwartz, 1977).

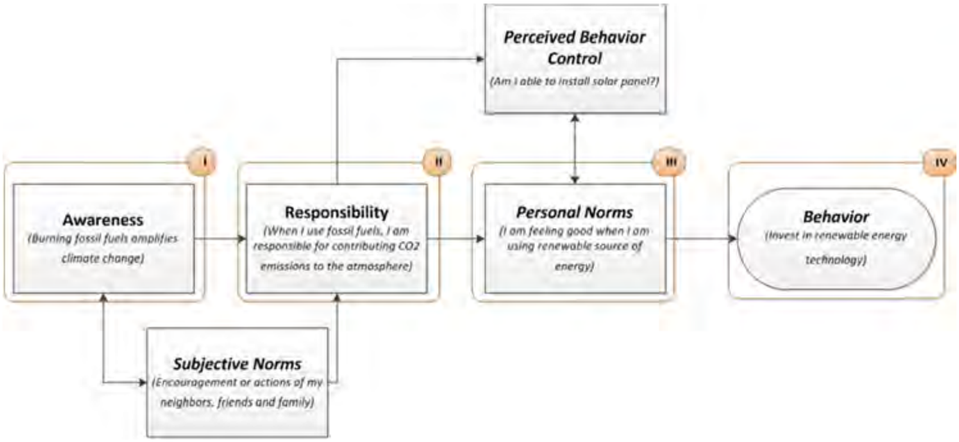


***Figure 3.1**: Conceptual representation of the Norm Activation Theory (Adapted from Schwartz 1977, De Groot and Steg 2009). A decision-making process leading to a particular behaviour follows 5 main consecutive factors: awareness, responsibility, personal norms, subjective norms and perceived behaviour control. In order to reach to a particular behaviour (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 behaviour control (the linking box II- III) indicates an extent, to which performing a particular behaviour could be easy or difficult for an individual. Finally, personal norms (box III) represents a moral obligation triggering the behavioural change.*

To be able to reach a decision to pursue a particular behaviour (Box IV, Fig. 3.1), an individual first needs to be aware of a problem (Box I, Fig. 3.1). A sufficient level of awareness then leads to understanding own individual responsibility, i.e. the consequences of own actions (Box II in Fig. 3.1). Subjective norms (that link Box I and II in Fig. 3.1) account for the perceived social pressure to engage or not to engage in a particular behaviour, e.g. solar panel installation in a neighbourhood 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 neighbours 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 behaviour control (the link between Box II-III). Perceived behaviour control (PBC) characterizes the extent, to which performing a particular behaviour 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 behaviour change or not.

3.3. Methodology

To investigate cumulative impacts of behavioural changes of households and their potential contribution to shifts in a regional residential energy demand, we integrate behavioural 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 (Figure 1), form a solid basis for our analysis. Empirical behavioural 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 3.3.1). The Behavioural 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 3.3.2). To reach any of the three decisions, household agents in *BENCH* go through a decision-making process, which includes several stages (Figure 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 behavioural process of decision-making among households who consider energy-related decisions based on solid theoretical and empirical ground.

3.3.1. 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=755 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 behavioural 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 3.2) assumes three main steps that lead to one of these actions: knowledge activation, motivation, and consideration (Figure 3.2). In each step, several psychological factors (e.g. awareness, personal norms, feeling guilt), economical (e.g. 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 (Figure 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 behavioural factors affecting these decisions.

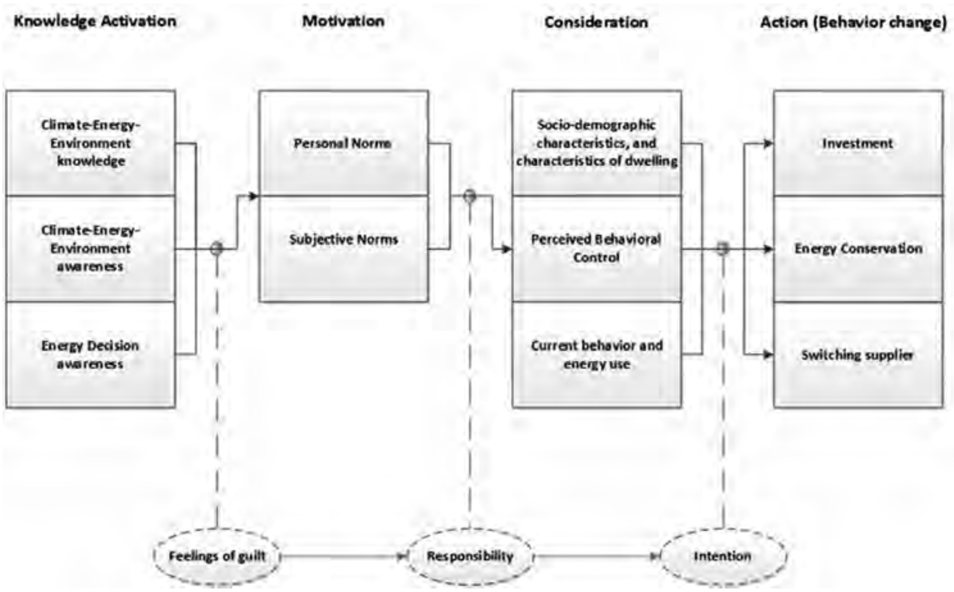


***Figure 3.2**: Conceptual model underlying the household survey*

Figure 3.2 indicates the stages behind each decision, i.e. behavioural 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 behaviour. 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 behaviour, 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 behaviour change of households.

Tables 3.3-5 provide a brief overview of the survey sample to illustrate the distribution of the most important factors – including the key behavioural variables – across various income groups. The variation in these factors among surveyed households, as registered in the 2016 responses, is used to initialize* a population of heterogeneous agents in the ABM (Section 3.3.2).

In addition to socio-demographic and energy use data (Table 3.3), we provide a summary of the distribution of behavioural factors (Table 3.4) and undertaken energy use choices (Table 3.5) reported by the households in our sample. The behavioural factors listed in Table 3.4 are measured by means of a questionnaire in our survey (please see examples of the questions used to elicit these behavioural factors in Appendix A). Data from Tables 3.3 and 3.4 is used to parameterize behavioural rules in the BENCH model as discussed further in Section 3.3.2.

* 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.

Table 3.3: *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, Primary Secondary Tertiary BSc MSc 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, A B C D E F							
House owner, % in each income group	37%	78%	85%	94%	96%	86%	80%

***Table 3.4:** 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 3.5 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 behaviour 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.

Table 3.5: *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
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

3.3.2. 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 behavioural 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 Modelled 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 Modelled explicitly within the model to enable market dynamics, in particular the market clearing procedure, and to trace feedbacks between individual household behavioural 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 behavioural characteristics from the survey data, using either averages or the exact empirical distributions depending on the simulation experiment (Table 3.6). To expand our 755 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 behavioural characteristics from the survey data summarized per income class in Tables 3.3, 3.4 and 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.

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 Figure 3.4, 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 behaviour (Box II), and consideration levels (Box III) when they perform costs and utility assessments. This decision process closely follows the conceptual NAT-based framework (Figure 3.1) behind the household survey (Figure 3.2) and applies to all the three groups of energy-related actions (Table 3.1). 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.

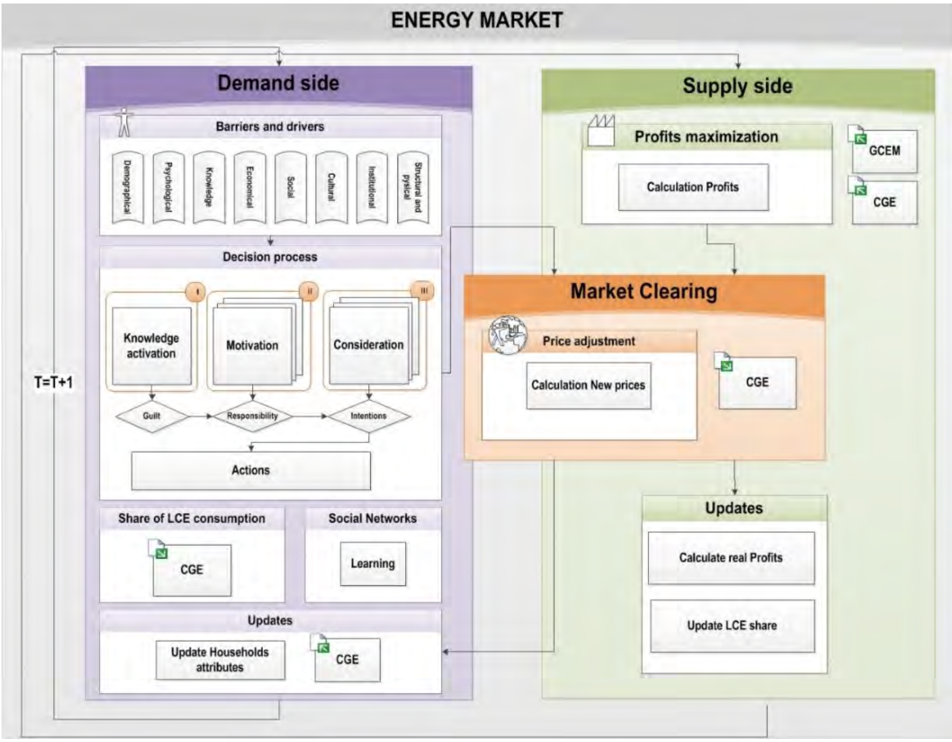


Figure 3.3: Representation of the dynamics flows within the BENCH model

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.

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

Further, on each time step household agents calculate their current individual level of *knowledge and awareness* (Low or High) based on the *K* value (equation 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, Eq2).

(2)

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

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 (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, equation 3) is measured based on consideration factors.

(3)

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

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 behavioural 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 3.3.1 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* (Z) under budget constrains (Eq.6):

(4)

$$U = \alpha . Z + \beta . E$$
$$E = Q \, . \, P$$

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 equations (1)-(3):

(5)

$$U = \alpha . Z + \beta . E + K + M + C$$

* A composite good is a typical assumption in microeconomics (Varian, H.R. (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.

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 (θ^e), and 3 (θ^p):

(6)

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

Hence, both behavioural 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 behavioural control assessment initialized from the survey data. Secondly, each individual utility is constrained by a household's budget (Eq. 4-6), which is shared between energy consumption and a composite good. The behavioural factors (Eq.5) just extend the traditional economically-constrained utility (Eq4.). 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:

(7)

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

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

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* 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 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 Modelling implies that (i) only aggregated annual demand and supply are compared excluding a possibility to study behaviour 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 Modelled 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):

---

* The EXIOMOD CGE model is designed at TNO in the Netherlands. https://repository.tudelft.nl/view/tno/uuid:3c658012-966f-4e7a-8cfe-d92f258e109b/

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

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

$$R = \mathrm{CPG} * \mathrm{P} * \mathrm{Q} \tag{9}$$

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.

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

Each time step t households and electricity provider agents make their decisions based on these price expectations (P_t^e), which are 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, Eq. 4-6) based on the expected price (P_t^e, Eq. 10) and follow a satisfying behaviour 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 & Filatova, 2016). Hence, there is always a possibility of a behavioural change at the individual level driven by updates in expectations, prices and behavioural 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).

3.3.3. Experiments setup

In line with the research question, we design several model experiments (Table 3.6). 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 behavioural 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 behavioural actions among households over time, and the changes in saved energy and CO_2 emissions.

Table 3.6: *Experiments setting*

Factors	Var	Exp1 Economic factors: homo; Behavioural factors: no; Learning: no	Exp2 Economic factors: hetero; Behavioural factors: no; Learning: no	Exp3 Economic factors: hetero; Behavioural factors: homo; Learning: no	Exp4 Economic factors: hetero; Behavioural factors: hetero; Learning: no	Exp5 Economic factors: hetero; Behavioural factors: hetero; Learning: 1	Exp6 Economic factors: hetero; Behavioural 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)

Psychological factors	**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)
	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)

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 behavioural attributes and behavioural heterogeneity (Exp3, Exp4): Individual decisions, including energy use choices, could be influenced by behavioural 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 behavioural 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 behavioural 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 behavioural factors, which are rarely directly observable and are often omitted when Modelling energy demand. In Exp3 we initialize the population of agents using the survey data on household behavioural 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 behavioural 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 behaviour 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 Modelling 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 neighbours 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 awareness and motivation (CEEK, CEEA, EDA, PN, SN, Exp5 and 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 behavioural factors – awareness and motivation – with those of their 8 closest neighbours, 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.

3.4. Results and Discussion

In what follows, we present the results of the *BENCH* model by tracking individual and cumulative impacts of behavioural 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.

3.4.4. 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 behavioural 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 behavioural 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 3.6). Thus, agents from different income groups residing in houses of different quality are still homogenous in terms of their behaviour decision process. Figure 3.4 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 3.5). 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), fuelling 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.

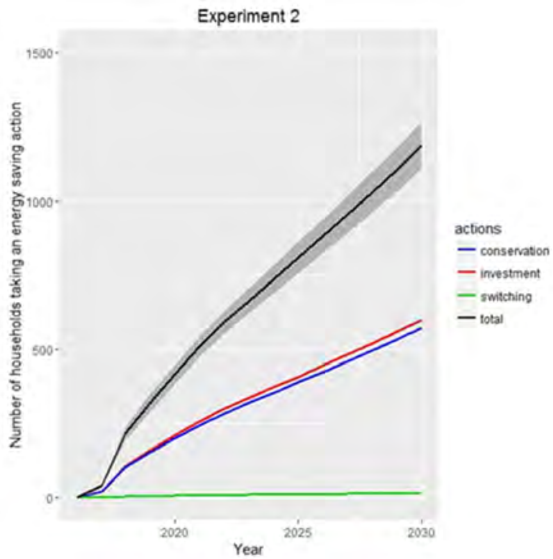


Figure 3.4: *Diffusion of energy-related actions among household heterogeneous economic and housing attributes (Exp2). The grey bounds around the curves indicate the uncertainty intervals across 100 Monte Carlo runs.*

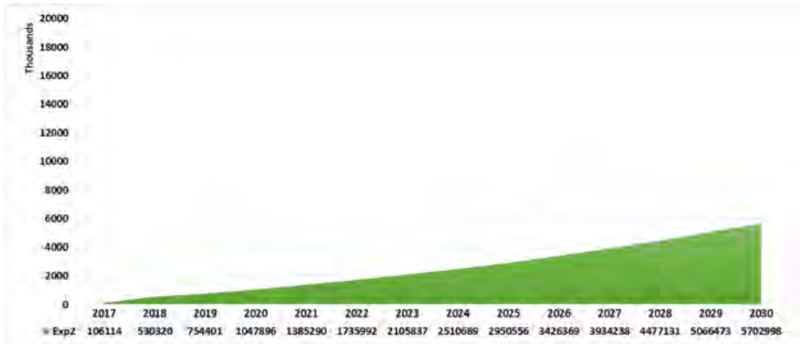


Figure 3.5*: Cumulative saved energy (kWh) by heterogeneous (in economic and physical and housing attributes) households' energy-related actions (Exp2).*

Figure 3.5 presents the amount of the saved energy (kWh) due to the households' energy-related actions reaching up to 6000 kWh by 2030. The saved electricity (kWh) is unequally distributed among various income groups and various types of energy-efficiency of buildings (Table 3.7). 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 behaviour. 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 behavioural change actions.

Table 3.7: *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%)

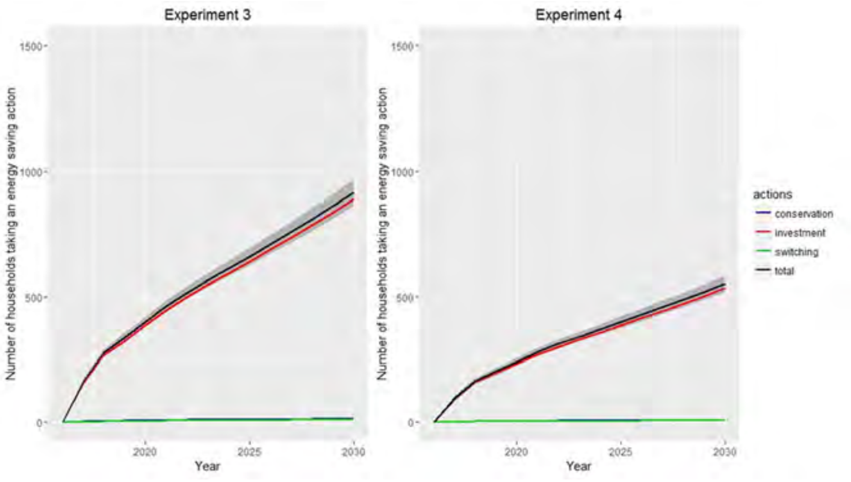
Dwelling energy label	A	461 (30%)	2572 (30%)
	B	***444 (29%)***	***2390 (28%)***
	C	290 (19%)	1610 (19%)
	D	166 (11%)	968 (11%)
	E	85 (6%)	7550 (6%)
	F	***73 (5%)***	***382 (5%)***

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 behaviour 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 specific action (Figure 3.2), we run the next set of experiments with our ABM.

3.4.5. The role of behavioural heterogeneity: psychological factors

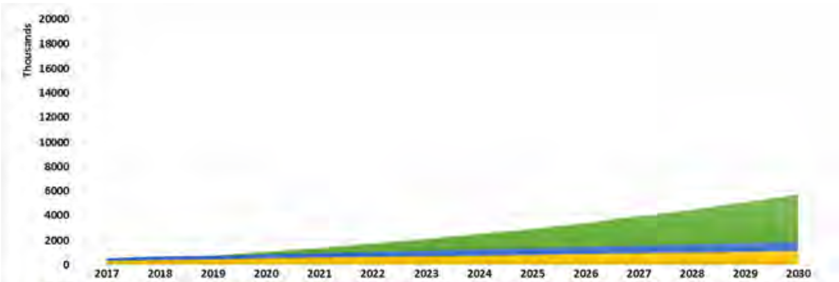
To quantify individual psychological drivers in household energy-related decisions and the cumulative impacts of these decisions, we compare Exp3 and 4. Both experiments extend Exp2 by adding the knowledge activation and motivation stages in household decision process (Section 3.3.1), thus Modelling 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 3.6, 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 3.6). The outcomes of Exp3 indicate what happens if we explicitly assume that decision-making is a process influenced by behavioural 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[*]. Exp4 demonstrates a scenario when individual households process these steps in a heterogeneous manner. Neither Exp3 nor 4 considers any learning processes (Table 3.6).

[*] We also ran a scenario with activating both behavioural 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 behaviour process matters only when it is heterogeneous (Exp3 and 4).



(a) *(b)*

Figure 3.6: *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 behavioural changes in a population of agents with diverse awareness and knowledge activation but homogeneous motivation. (Exp3); (b) Propagation of the 3 types of behavioural 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

Figure 3.7*: Saved energy in kWh (Experiment 3, 4 and Experiment 2 as a benchmark).*

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 (Figure 3.6) 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 3.3.2). 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 3.8 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 behaviour. Figure 3.7 illustrates how much energy heterogeneous households could save cumulatively by changing their behaviour in the presence of behavioural 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 behavioural barriers. In other words, we might be employing just between 20-36% of the energy saving potential that individual behavioural changes have to offer. This illustrates the extent and importance of addressing the psychological aspects of potential individual behavioural changes with respect to energy use.

***Table 3.8:** Distribution of the climate mitigation efforts among various socio-economic groups and dwelling types, assuming households are affected by psychological factors and may exhibit behavioural heterogeneity (Exp3 and Exp4). MWh (percent (%), contribution of each individual group in total saved energy)*

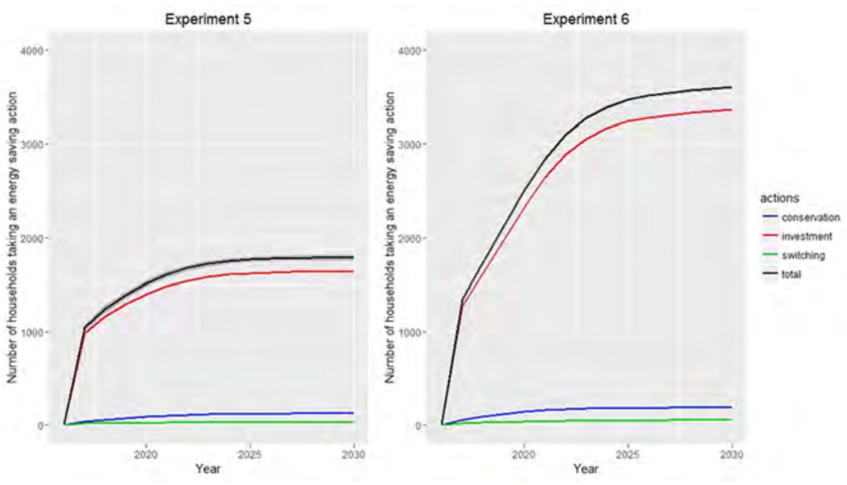
Socio-economic groups		**Cumulative saved electricity,** in MWh			
		2020		**2030**	
Experiments		**Exp3**	**Exp4**	**Exp3**	**Exp4**
Income groups (in thousands euro per year)	1 (< 10)	173 (11%)	79 (10%)	471 (12%)	325 (15%)
	2 (10-30)	***468 (31%)***	***235 (28%)***	***1546 (40%)***	***843 (40%)***
	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%)	764 (20%)	458 (24%)
	B	***508 (34%)***	***235 (28%)***	***1269 (33%)***	***672 (34%)***
	C	438 (29%)	224 (27%)	960 (25%)	424 (22%)
	D	164 (11%)	105.4 (13%)	436 (11%)	219 (11%)
	E	114 (8%)	71.4 (8.6%)	290 (8%)	122 (6.3%)
	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%)

Table 3.8 reports the distribution of saved electricity (MWh) gained through the energy-related behaviour 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.

3.4.6. The role of learning process and social network

Previous experiments study the diffusion of the three types of energy-related behaviour 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 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.



(a) (b)

***Figure 3.8**: 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).*

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 neighbours, which can either raise or lower knowledge and awareness regarding LCE. Figure 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.

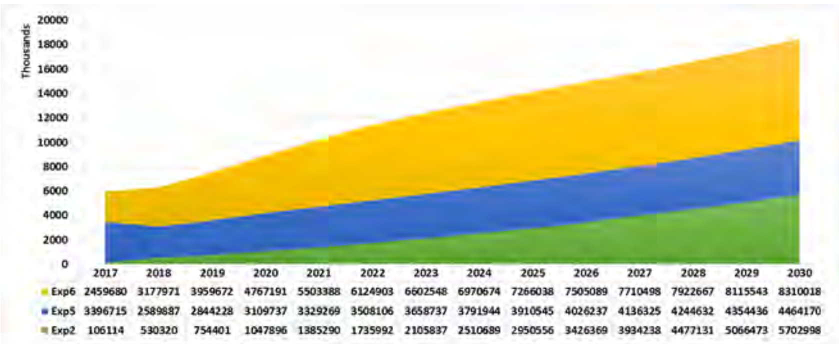


Figure 3.9: *Saved energy in kWh (Experiments 5, 6 and Experiment 2 as a benchmark). It shows that adding social network and learning in knowledge activation stage (Exp5) and then in knowledge activation and motivation stages (Exp6) helps households to save more energy by changing their behaviour. For instant, following the Exp6 strategy, households could save approximately 3800 MWh more energy.*

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 (Figure 3.8b). 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 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 (Figure 3.9).

Table 3.9: *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%)

Notably, when social learning takes place the uptake of Actions 1-3 continues in all income groups (Table 3.9) and is most popular among owners of houses with the energy label B, as before (Tables 3.7 and 3.8).

3.4.7. Macro impacts of individual energy-related behavioural changes

Figure 3.10 summarizes the outcomes of all the experiments in terms of diffusion of energy-related behavioural 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 behavioural changes in a society. The gray 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 behavioural 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 (Figure 3.11). 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 footprint. Figure 3.12 presents the dynamics of the cumulative CO_2 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.

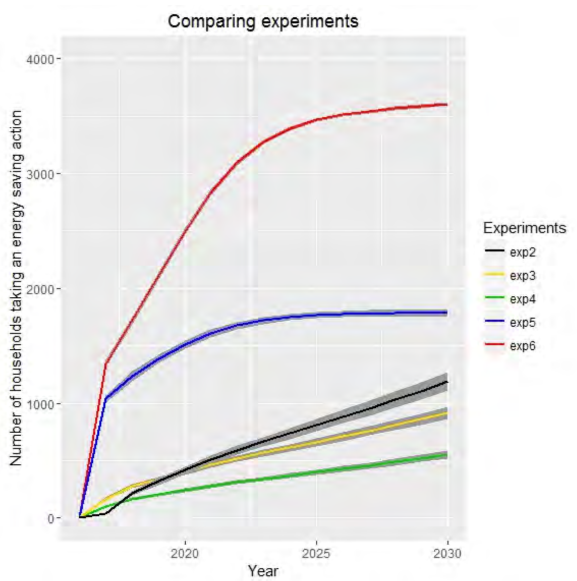


Figure 3.10: *Diffusion of households' energy-related actions measured as the total number of households pursuing either investment, conservation or switching. A baseline Experiment 2 (in black) assumes that households are heterogeneous in economic and housing attributes. Adding psychological factors and, thus behavioural 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).*

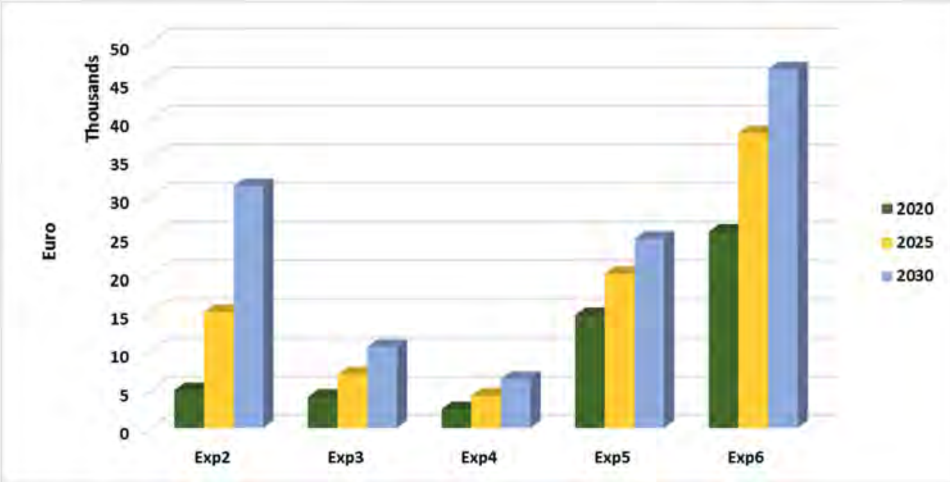


Figure 3.11: *Cumulative/Regional economic net savings as a result of individual households energy-related actions, in euro*

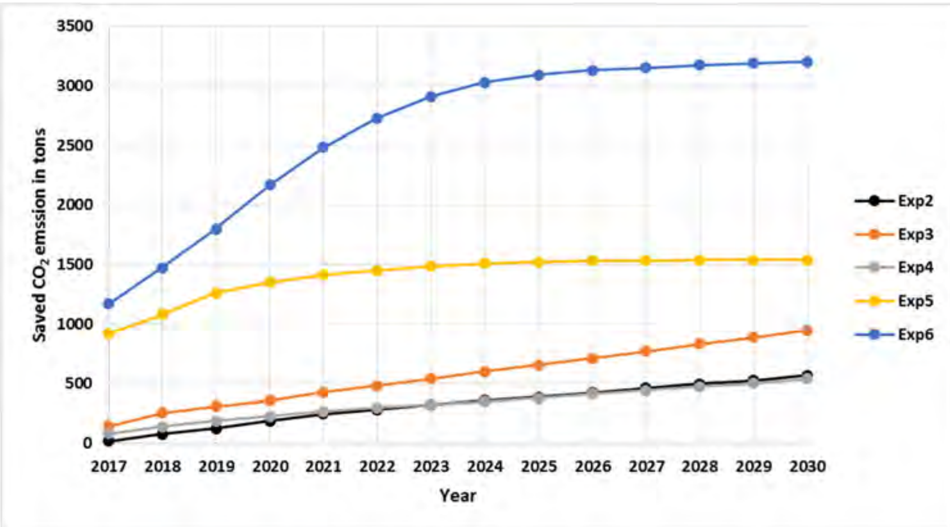


Figure 3.12: *Saved CO_2 emissions (in tons) resulting from households energy-related investments (installing solar panels)*

3.5. Conclusions and policy Implications

Promoting energy efficient behaviour of households is a major challenge and an opportunity for policy-makers. The potential of reducing emissions through behavioural 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 behavioural 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 behavioural 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 behavioural 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 behavioural 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 behavioural changes of households and aggregated provincial impacts of these changes.

We report that pro-environmental individual energy choices and behavioural 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 behavioural 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 (Figure 3.11) and preventing more than 3200 tons of CO_2 emissions (Figure 3.12). In line with the survey data (Table 3.5), 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 behaviourally 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 behavioural changes more points-of-action can be discerned than just making the energy saving alternatives more attractive, financially or otherwise. The presence of behavioural barriers can diminish the potential for energy and emission savings by anywhere between 63%-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 modelling of both demand (e.g. account for discounting) and supply (production costs, tariffs, technological learning). The theoretically and empirically grounded Modelling 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 behavioural aspects. Understanding the cumulative impacts of behavioural 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 behavioural changes regarding energy use.

Appendix A

In 2016 we ran a household survey over an extensive sample of respondents, N=755 households, using an online questionnaire in Navarre province, Spain*. 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†. 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 3.A.1 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.

* Navarre is a province in northern Spain, and consists of 272 municipalities.

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

***Table 3.A.1**: 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%

We designed the survey based on the environmental psychology literature to identify potential factors of households' energy-related behavioural 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 3.2) assumes three main steps that lead to one of these actions: knowledge activation, motivation, and consideration. Survey questions used to measure the behavioural factors relevant for energy use choices of individual households. Following tables (A.2-4) 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 3.3.2). To measure each of these items (*CEEK, CEEA, EDA*) we rely following questions, inspired by the standard measures used in the behavioural literature. Table A.2 shows example questions of each knowledge activation items.

Table 3.A.2: *Knowledge activation items*

Knowledge and awareness (K)
Climate-Energy-Economy Knowledge
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
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
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")

Motivation (M) as presented in Section 3.3.2, is evaluated based on *Personal norms (PN)* and *Subjective norms (SN)*. Table 3.A.3 brings example questions that we asked to measure *PN* and *SN*.

Table 3.A.3: *Motivation items*

Motivation
Personal Norms (PN)
To what extent do you agree or disagree with each of the 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”)*

Consideration (C) is measured based on the level of *perceived behaviour control* which is differ in three actions (*PBC1, PBC2, PBC3*) and *Energy-efficient habits and patterns (HEP)*. Table 3.A.4 shows example questions that we asked households to measure their *PBC* based on three actions and their conservation habits and patterns.

***Table 3.A.4**: Consideration items*

Consideration
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 produce 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”)

Chapter 4:

THE MACRO IMPACT OF INDIVIDUAL ENERGY BEHAVIOURS ON CARBON EMISSIONS: A NETHERLANDS CASE STUDY

Niamir, L., Kiesewetter, G., Wagner, F., Schöpp, W., Filatova, T., Voinov, A. & Bressers, H.

Climatic Change (Under review)

Parts of this chapter also appeared in:

- Niamir, L., et al. (2018). Impact of households' behavioural change on the energy demand in a transition to low-carbon economy. IAEE International Conference, 10-13 June, Groningen-The Netherlands.
- Niamir, L., et al. (2017). From Households' Energy-Efficient Choices to Air Quality and Climate. International Conference of Impacts World 2017, 11-13 October, Potsdam, Germany.
- Niamir, L., et al. (2017). Household Energy Use and Behaviour Change Tracking Framework: From Data to Simulation. Conference on Complex Systems, 17-22 September, Cancun-Mexico.

Abstract

In the last decade, instigated by the Paris agreement and United Nations Climate Change Conferences (COP22 and COP23), the efforts to limit temperature increase to 1.5°C above pre-industrial levels are expanding. The required reductions in greenhouse gas emissions imply a massive decarbonization worldwide with much involvement of regions, cities, businesses and individuals in addition to the commitments at the national levels. Improving end-use efficiency is emphasized in previous IPCC reports (IPCC, 2014b). Serving as the primary 'agents of change' in the transformative process towards green economies, households have a key role in global emission reduction. Individual actions, especially when amplified through social dynamics, shape green energy demand and affect investments in new energy technologies that collectively can curb regional and national emissions. However, most energy-economics models (usually based on equilibrium and optimization assumptions) have a very limited representation of household heterogeneity and treat households as purely rational economic actors. This paper illustrates how computational social science models can be used to address this gap. We demonstrate the usefulness of such behaviourally-rich agent-based simulation models by simulating various behavioural and climate scenarios for residential electricity demand and compare them with the business as usual (SSP2) scenario. Our results show that residential energy demand is strongly linked to personal and social norms. The intensity of social interactions and learning plays an equally important role for the uptake of green technologies as economic considerations, and therefore in addition to carbon-price policies (top-down approach), implementing policies on education, social and cultural practices can significantly reduce residential carbon emissions.

4.1. Introduction

The efforts to limit temperature increase to 1.5°C above pre-industrial levels are expanding supported by United Nations Climate Activities[*]. In order to limit global warming to this critical level, they set an aim to achieve a balance between sources of anthropogenic emission and sinks of greenhouse gases in the second half of this century[†]. Electricity generation from fossil fuels contributes the second largest share (28.4%) of global greenhouse gas emissions[‡]. Decarbonization of the economy will require massive worldwide efforts and strong involvement of regions, cities, businesses and individuals in addition to the commitments at the national levels (Grubler et al., 2018). Public climate mitigation efforts should ideally be aligned with private interests to improve the speed and efficiency of this process. Individual actions, especially when amplified through social dynamics, shape green energy demand and affect investments in new energy technologies that collectively can curb regional and national emissions. Serving as primary 'agents of change' in the transformative process towards green economies, households play a key role in global emissions reduction. Hence, there is a demand for tools that, next to economic considerations, can assess their cumulative emissions given the diversity of behaviour and a variety of psychological and social factors influencing it.

[*] United Nations Climate Change Conferences: COP21-23

† The Paris agreement

https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement

[‡] U.S. Energy Information Administration (2016). Electricity Explained – Basics
https://www.eia.gov/energyexplained/index.php?page=electricity_in_the_united_states

The International Energy Agency (IEA) reported that the global energy-related carbon dioxide emissions stagnated for a third straight year in 2016*. This is a result of growing renewable power generation, a switch from coal to natural gas, as well as improvements in energy efficiency and end-user awareness. Subsidies, an emissions trading system, renewable energy standards, and other instruments have been developed to reduce emissions on the supply side of the energy market. Although economic incentives are effective mechanisms to influence energy producers, mechanisms to affect the demand side are less straightforward (Creutzig et al., 2018a; Zhang et al., 2017). Given the scale of the impact that households' choices have on energy consumptions and emissions, it puts them at the epicenter of the international policy and research agenda†.

Bin and Dowlatabadi (2005) report that more than 40% of total CO_2 emissions in United States is directly influenced by households' activities; Baiocchi et al. (2010) show around 52%, or 358 million tones CO_2 emissions come through indirect household consumption in United Kingdom. As households get greater awareness of the value and the need for sustainable energy practices, the public concerns on climate change and energy-related behaviours are slowly growing. Some first rough assessments indicate that behavioural change alone can contribute to 4%-8% (Faber et al., 2012; McKinsey, 2009) of overall CO_2 emissions reduction. Gadenne et al. (2011) study the influence of consumers environmental beliefs and attitudes on energy-related behaviours and find that people have been paying more

* https://www.iea.org/newsroom/news/2017/march/iea-finds-co2-emissions-flat-for-third-straight-year-even-as-global-economy-grew.html

† Cities and Climate Change Science Conference, Edmonton-Canada, March 5-7, 2018

https://www.ipcc.ch/meetings/cities/

attention to environmental issues nowadays, while many efforts have been made to promote a green consumer lifestyle.

Only limited tools are available to assess their cumulative emissions given the diversity of behaviour and a variety of psychological and social factors influencing it beyond pure economic considerations (Niamir et al., 2018b). Many macro models, e.g. general equilibrium models are predominately used to support climate change policy debates, particularly in the economics of climate change mitigation (Babatunde et al., 2017). These models usually assume that economic agents form a representative group(s), have perfect access to information and adapt instantly and rationality to new situations, maximizing their long-run personal advantage. However, in reality people make decisions driven by their diverse preferences, shaped by socio-economic conditions, behavioural biases and social peer influence (Farmer and Foley, 2009). Therefore, policymakers require supporting decision tools, that may explore the interplay of economic decision-making and behavioural heterogeneity in households' energy choices when testing common climate mitigation policies (e.g. carbon pricing) and socio-economic pathways in a world with changing climate (e.g. SSPs).

The aim of this article is to provide such tools through a combination of a new bottom-up simulation method grounded in an empirical survey to extract heuristic rules on energy consumption behaviour for individual agents. For this purpose, we use an agent-based model in which the agents – individual households with detailed socio-economic characteristics – are taking decisions about a range of realistic actions related to their household electricity supply while being exposed to economic (e.g. carbon price) as well as psychological and social pressures (e.g. promotion of green electricity).

After introducing the methodology in Section 4.2, we present in Section 4.3 results from an analysis of different micro-scenarios of households in a European region (Overijssel, Netherlands) up to the year 2030. We quantify the changes in household electricity demand from conventional and green suppliers when varying psychological as well as economic incentive parameters. While we focus on one region as a proof of concept here, there are several ways to upscale and cover larger areas (Niamir et al., 2018c).

4.2. Methodology

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 detailed micro-simulation models for a specific technology (Bhattacharyya, 2011; Hunt and Evans, 2009). Agent-based modelling (ABM) is a powerful tool for representing the complexities of energy demand, such as social interactions and spatial constraints and processes (Farmer and Foley, 2009; Filatova et al., 2013). Unlike other approaches, ABM is not limited to perfectly rational agents or to abstract micro details in aggregate system-level equations. Instead, ABM can represent the behaviour of energy consumers – such as individual households – using a range of behavioural theories. In addition, ABM has the ability to examine how interactions of heterogeneous agents at micro-level give rise to the emergence of macro outcomes, including those relevant for climate mitigation such as an adoption of low-carbon behavioural strategies and technologies over space and time (Rai and Henry, 2016). The ABM approach simulates complex and nonlinear behaviour that is intractable in equilibrium models.

To assess the impact of individual behaviour on carbon emissions, we went beyond classical economic models and the stylized representation of a perfectly informed optimizer. Therefore, we further developed the *BENCH*[*]

[*] The Behavioural change in ENergy Consumption of Households (*BENCH*) agent-based model

agent-based model (Niamir et al., 2018b) by strengthening the alignment of behavioural and economic factors under different climate policy scenarios. We calibrated the *BENCH-v.2* model using data on households' energy-related choices from a survey specially designed for this purpose (Section 4.2.3) and administered in a European region of Overijssel, The Netherlands (1383 households). The *BENCH-v.2* calculates changes in electricity consumption annually and implied carbon emission -based on the primary source of energy- by simulating individuals' behaviours (Section 4.3).

4.2.1. Overview: individual energy behaviour

There is a number of energy-related actions which individuals may pursue to influence their electricity consumption and, consequently, their carbon footprint. We categorize them into three main types of behavioural changes. An individual can make an investment (action A1), either large (such as installing solar panels) or small (such as buying energy-efficient appliances, e.g. A++ washing machine). Alternatively, individuals can save energy by changing their daily routines and habits (action A2) -e.g. by switching off the extra lights and adjusting a thermostat/air conditioner. Finally, households can switch to a supplier that provides green electricity (action A3) (Niamir and Filatova, 2017).

Driven by the empirical evidence from environmental behavioural studies (Abrahamse and Steg, 2011; Bamberg et al., 2007; Bamberg et al., 2015; Mills and Schleich, 2012; Onwezen et al., 2013; Steg and Vlek, 2009), the *BENCH-v.2* model assumes that a decision regarding any of the three actions (A1-A3) is driven by psychological and social factors in addition to the standard economic drivers such as prices relative to incomes (Niamir et al., 2018b). Behavioural factors including personal norms and awareness may either amplify the economic logic behind a decision-making or impede it, serving either as a trigger or a barrier (Figure 4.1). It is a scientific challenge to combine the behavioural (emotional) and the economic parts of the decision-making process in a formal model. Here we present the simplest option assigning weights to the behavioural part by calculating households intentions toward a specific energy-efficient action derived from our household survey dataset.

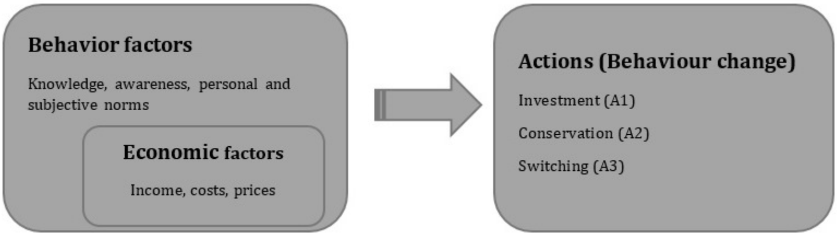


***Figure 4.1**: Factors affecting household decision-making regarding their energy use*

4.2.2. Survey and empirical data

Our household survey is designed to elicit factors and stages of a decision-making process with respect to the three types of actions that households typically make (A1 investment, A2 conservation and A3 switching). The conceptual framework behind the survey assumes three main steps that lead to one of these actions: knowledge activation, motivation, and consideration (Niamir et al., 2018b). Before considering action, households need to reach a certain level of knowledge and awareness about climate change, energy and the 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 households get motivated, they feel responsible to do something. Still, none of these factors are enough to provoke an action to change the energy use behaviour. A household needs to consider its economic status, its house conditions (e.g. renting of owning), its current habits, and own perception of its ability to perform an action or change behaviour. If a household reaches a certain level of intention, it is going to decide or act.

To elicit data on an interplay of behavioural and economic factors, we conducted a survey in a European region (NUTS2 level) in 2016: Overijssel province in The Netherlands (NL21), see Figure 4.2. The data on the behavioural and economic factors affecting household energy choices were collected using an online questionnaire (N= 1,035 households in Overijssel) and serve as empirical micro-foundation of agent rules in the *BENCH-v.2* model. The variations in socio-demographic and psychological factors among the respondents are further used to initialize a population of heterogeneous agents in the ABM (Section 4.2.3). The differentiation per income group also allows to potentially connect with other micro and macro statistical data if needed.

***Figure 4.2**: Survey case study: Overijssel province-The Netherlands*

4.2.3. BENCH agent-based model

Compared to its first version (Niamir et al., 2018b), the *BENCH* ABM has been further developed and modified to investigate the macro impact of cumulative individual behavioural change on carbon emissions. In particular, in this application we extended *BENCH* by: (a) introducing three representative electricity producers (grey, green and super green); (b) further improving the model engine, which now treats behavioural and economical parts explicitly (Section 4.2.1). In the behavioural part, the psychological and social aspects of a household's behaviour change and decision making are evaluated (Section 4.2.3). If there is high intention, household agents proceed with assessing the typical economical utility (Section 4.2.3). In the economical part households' utilities based on the three actions(A1-A3) are calculated and compared (Figure 4.3).

Further changes compared to the original *BENCH* include: (c) improvements in social dynamics and learning algorithms by introducing and simulating two ways of households' interactions (Section 4.2.3); (d) running a carbon price scenario as a top-down strategy to investigate impacts of policies on household behavioural change (Section 4.2.3); (e) the results of simulations in terms of CO_2 emissions (tones per capita) to compare between scenarios (Section 4.3.1) to get a better overview on the impacts of individuals' behaviour on carbon emissions over time and space. The role of each action (A1-A3) in these trajectories is also estimated till 2030 (Section 4.3).

Household agents in *BENCH-v.2* are heterogeneous in socio-economic characteristics, preferences, and awareness of environment and climate change, so they can pursue various energy-efficient choices and actions. Namely, they vary in six economic attributes: (1) annual income in euro, (2) annual electricity consumption in kWh, (3) household status in terms of being a grey, green or super green electricity user, (4) dwelling tenure status - owner or renter; (5) energy label of their dwelling varying from A to F; and (6) the household energy use routines and habits measured in the survey in terms of frequency of performing a particular energy-consuming action. Data for all these variables come from the survey. The annual growth value of socio-economic variables representing households' income, electricity consumption, and consumption of other goods (in 5 quintiles) for the Overijssel province comes from the EXIOMOD[*] computable general equilibrium (CGE) model (Filatova et al., 2014). The behavioural and social aspects impacting households energy decisions also vary among agents and include: (1) personal norms[†], which are values that people hold (Schwartz, 1977), e.g. feeling good when using energy efficient equipment; (2) subjective norms[‡], which are perceived social pressure on whether to engage in a specific behaviour motivated by observing energy-related actions of neighbors, family and friends'; and (3) perceived behavioural control (Section 4.2.3). These behavioural and social variables are updated over time (annually) through social dynamics and learning procedures (Section 4.2.3). Agents' decision processes closely follow the conceptual framework (Figures 1 and 3) behind the household survey and apply to all three types of energy-efficient behaviours (A1-A3).

Behaviour part

Based on different internal and external barriers and drivers, households have different knowledge and awareness levels about the state of the climate and environment, motivation levels to change their energy behaviour, and

[*] Within the COMPLEX project funded by the EU FP7 program, the BENCH model was integrated with a CGE EXIOMOD. The EXIOMOD CGE model is developed at TNO in the Netherlands. https://repository.tudelft.nl/view/tno/uuid:3c658012-966f-4e7a-8cfe-d92f258e109b/

[†] Personal norms are attached to the self-concept and experienced as feelings of a moral obligation to perform a certain behavior (Schwartz, S.H., (1977) Normative Influences on Altruism1, in: Leonard, B. (Ed.), Advances in Experimental Social Psychology. Academic Press, pp. 221-279.)

[‡] Subjective norms are determined by the perceived social pressure from others for an individual to behave in a certain manner and their motivation to comply with those people's views (Ham, M., Jeger, M., Frajman Ivković, A. (2015) The role of subjective norms in forming the intention to purchase green food. Economic Research-Ekonomska Istraživanja 28, 738-748.)

consideration levels when they perform costs and utility assessments. All household attributes are heterogeneous and change over time and space. All the variables in knowledge activation, motivation and consideration are measured in comparable ways using Likert scale, in the range of 1-7 as in the survey. Here 1 stands for the lowest, 7 is the highest level (Niamir et al., 2018a; Niamir et al., 2017).

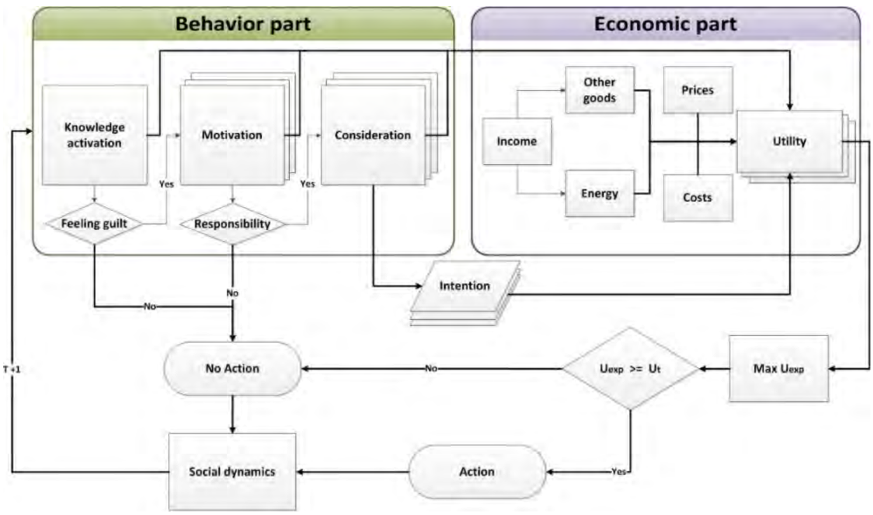


Figure 4.3: *A household's decision-making algorithm in the BENCH-v.2 agent-based model*

Niamir et al. (2018b) described how households' knowledge and awareness *(K)* and motivation *(M_n)* are measured and calculated at the model initialization stage based on the survey data. In summary, *K* is based on climate-energy-environment knowledge *(CEEK)*, climate-energy-environment awareness *(CEEA)*, and energy-efficient decision awareness *(EDA)* values. If households are aware enough, that is they have a high level of knowledge and awareness above the threshold of 5 out of 7, then they are tagged as "*feeling guilt*" and proceed to the next step to assess their motivation *(M_n)* for particular actions. Households' personal norms *(PN_n)* and subjective norms *(SN_n)* are assessed to calculate their motivation *(M_n)*. In this paper, motivation may differ for each of the three main actions (*n= {1,2,3}*). For example, a household may have a high level of motivation for installing solar panels, and is therefore tagged as "*responsible*" for action1 (investment) and proceeds to the next step (consideration). At the same time, it may not pass the threshold value in motivation for changing energy use habits or switching to another energy supplier, and thus does not go into the consideration step on those two actions. If household agents have a high motivation level and feel responsible, they consider the psychological (e.g. perceived behaviour control*), structural (housing attributes) and institutional factors (e.g. subsidies) to assess utility and costs of a specific action (Section 4.2.3). Then households with high level of consideration are tagged as "*high intention*". In the consideration stage, as well as the motivation stage, we differentiate between actions. In investment (A1) for instance, the dwelling ownership status (*SF*, owner or renter), and perceived behavioural control over the investment (PBC_1) are checked and evaluated (δ_1). While the ownership status is not essential in conservation (A2) and switching (A3), δ_2 and δ_3 are calculated just based on perceived behavioural controls (PBC_2 and PBC_3) All this is captured by the following equations:

(1)

$$K = \frac{AVG\ (CEEK, CEEA, EDA)}{7} \quad ;$$

$$M_n = \frac{AVG\ (PN_n, SN_n)}{7} \quad ;$$

$$If\ \ (n = 1\ and\ \ SF = 1)\ \ (\ \delta_1 = \frac{PBC_1}{7})\ \ else\ (\ \delta_1 = 0)\ \ ;$$

$$If\ \ (n = 2\ )\ \ (\ \delta_2 = \frac{PBC_2}{7})\ \ ;\ \ If\ \ (n = 3\ )\ \ (\ \delta_3 = \frac{PBC_3}{7})$$

---

* Own perception of her ability to perform an action or change behaviour.

Economic part

The economic part estimates utility of an individual agent for undertaking any of the three main actions. Energy economics (Bhattacharyya, 2011) assumes that households receive utility from consuming energy (E, here super green, green or grey) and a composite good (Z) under budget constraints:

$$U = Z \cdot \alpha + E \cdot (1 - \alpha) \tag{2}$$

Here α is the share of individual annual income spent on the composite good.

Niamir et al. (2018b) extend this standard utility by including the influence of knowledge and awareness *(K)* and motivation *(M_n)* and adding actions' intention *(δ_n)* as a weight on the behavioural part:

$$U = (Z \cdot \alpha + E \cdot (1 - \alpha)) \cdot (1 - \delta_n) + (K + Mn) \, . \, \delta_n \tag{3}$$

This weight is calculated and normalized using the survey data.

Social dynamics and learning

Heterogeneous households engage in interactions and learn from each other. In particular, they can exchange information with neighbours, which may alter own knowledge, awareness, and motivation regarding energy-related behaviour. Here we employ a simple opinion dynamics model (Acemoglu and Ozdaglar, 2011; Degroot, 1974; Hegselmann and Krause, 2002; Moussaid et al., 2015). Agents compare values of their own behavioural factors – knowledge, awareness, and motivation – with those of their eight closest neighbours, and adjust their values for a closer match. In different scenarios (Table 4.1), we introduce two types of interactions for households: slow and fast dynamics. Following the slow dynamics, households in an active neighbourhood[*] interact with maximally two neighbours (households 3 and 4 in figure 4.4.a), and a household(s) with lower than average value of the whole neighbourhood increases their current value by 5% (Figure 4.4.a). In the fast dynamics configuration, all households in an active neighbourhood exchange of opinions and learn from each other (Figure 4.4.b, Eq.4). In addition, the related perceived behaviour control (PBC_n) of a household that already took an action (household 5 in Figure 4.4) is raised by 5% (Eq.5).

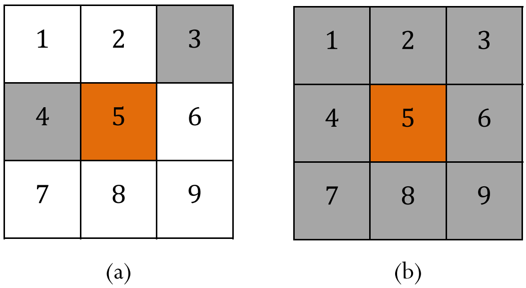


Figure 4.4: *Social dynamics and learning in an active neighbourhood where household "5" undertook an action at time t. (a) Slow dynamics: households 3 and 4 are affected and engage in social learning. (b) Fast dynamics: all households in the neighbourhood are affected and engage in social learning*

(4)

$$X = \{CEEK, CEEA, EDA, PN_n, SN_n\}, n = \{1, \dots 9\} \; ;$$
$$If\ Max\ (mean\ (X_n^t), median\ (X_n^t)) \geq X_3^t \quad (X_3^{t+1} = X_3^t + 0.05 \cdot X_3^t) \; ;$$
$$If\ Max\ (mean\ (X_n^t), median\ (X_n^t)) \geq X_4^t \quad (X_4^{t+1} = X_4^t + 0.05 \cdot X_4^t)$$

[*] An active neighbourhood is the one where at least one out of eight neighbours undertakes an energy-efficient action.

$$PBC_5^{t+1} = PBC_5^t + 0.05 \cdot PBC_5^t ; \quad (5)$$

Carbon emissions and pricing

In this research we investigate CO_2 emissions implied by households' electricity consumption which is supplied from power plants using different kinds of fuels. Carbon dioxide emission factors for electricity have been derived as the ratio of CO_2 emissions from fuel inputs of power plants relative to the electricity delivered. CO_2 emission factors of each fuel type are used as defined in IPCC (2006). Three different kinds of electricity suppliers are considered, between which the households can choose: "grey", "brown", and "green". The assumptions regarding fuel mixes and the resulting net CO_2 emission factors are listed in Table 4.1.

Table 4.1: *Fuel mix of supplier and CO_2 emission factors*

Supplier type	% Coal	% Gas	% Renewable	tCO_2/kWh
Grey	100	0	0	0.0009
Brown	0	100	0	0.0003
Green	0	0	100	0

To estimate the impact of climate policies, namely a carbon price, we design and add climate policy scenarios by including carbon price in the utility estimations of households.

4.2.4. End-user scenarios

Traditionally, rational optimization models such as CGE models, have been used to predict household energy consumption under various socio-economic scenarios including Shared Socioeconomic Pathways (SSP)[*]. Here the Baseline scenario represents this traditional economic setup where rational and fully-informed households make optimal decisions. Therefore, we use aggregated residential electricity consumption from the EXIMOD model downscaled to the regional level. The Baseline scenario (grey dash-line in Figures 4.5,4.6,4.9) is an output of this CGE model under SSP2 (business as usual).

We use this Baseline scenario as a benchmark to compare the output of our behaviourally rich ABM. Four end-user scenarios in *BENCH.v2* are designed to explore the impacts of heterogeneity in household attributes such as income and electricity consumption, social dynamics (bottom-up approach) and carbon price pressure (top-down approach) strategies on the individual and aggregated households behavioural change (Table 4.2). In all cases, based on the energy behaviour change of households, we assess the following macro-metrics: the diffusion of each of the three types of behavioural actions (A1-3) among households over time, and the changes in carbon emissions reduction.

[*] https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about

Table 4.2: *End-user scenario settings: Climate Policy and Human Behaviour scenarios*

***BENCH.v2* scenarios**	**Social dynamics**	**Carbon Price**
Scenario SD	Slow dynamics *In an active neighbourhood: households interact with maximum two neighbours*	-
Scenario FD	Fast dynamics *In an active neighbourhood: households interact with all available neighbours*	-
Scenario SDC	Slow dynamics *In an active neighbourhood: households interact with maximum two neighbours*	25 Euro/ton by 2030
Scenario FDC	Fast dynamics *In an active neighbourhood: households interact with all available neighbours*	25 Euro/ton by 2030

4.3. Results and discussion

We present the results of the *BENCH.v2* simulations by tracking individual and cumulative impacts of behavioural changes on carbon emissions among 1383 individual households in the Overijssel provinces 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).

4.3.1. Behavioural scenarios

In scenario SD the heterogeneous households with various income, electricity consumption, and dwelling conditions go through a cognitive process to decide whether to pursue any behavioural change or not. Figure 4.5 shows that introducing heterogeneity to the household economic and housing attributes leads to a reduction in carbon emissions resulting from changes in the residential electricity consumption in comparison to the baseline (grey dash-line), CO_2 emissions resulting from residential electricity consumption decrease 5% by 2030 by simply adding heterogeneity in household attributes and preferences. The decrease indicates a difference between a scenario with a representative agent vs the one where we disaggregate a representative consumer assuming a distribution of economic and housing attributes and interactions among households in the neighbourhood (Figure 4.5-black line).

Scenario FD shows what happens if we have more intense social dynamics within a neighbourhood – households have more opportunities to interact and learn – therefore the diffusion of information is faster inside society. The blue line in Figure 4.5 illustrates the impact of fast social dynamics alone, which delivers another 4.3% more reduction in carbon emissions by 2030 compared to scenario SD.

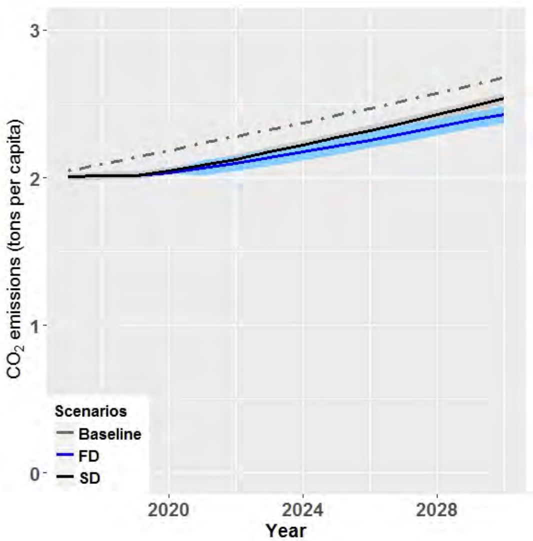


Figure 4.5: *Macro impact of heterogeneous households behavioural change on CO_2 emissions over time. Behavioural scenarios (SD, FD) and baseline scenario (2017-2030). The shaded bounds around the curves indicate the uncertainty intervals across 100 runs.*

Table 4.3: *Avoided CO_2 emissions (tons per capita) resulting from households energy-efficient actions, share of each action is reported in parenthesis; under behavioural scenarios (SD,FD), 2030.*

Actions	*Scenarios*	
	SD	***FD***
A1: Investment	0.01 (9.3%)	0.03 (10.7%)
A2: Conservation	0.04 (26%)	0.08 (26.1%)
A3: Switching	**0.10 (64.8%)**	**0.20 (63.3%)**

Table 4.3 shows which actions (A1-A3) contributed the most to the cumulative CO_2 emission savings. Our results indicate that such behavioural changes as investments in solar panels (A1) may deliver between 9%-11%, conserving electricity by using less or changing their daily habits and usage patterns (A2) and switching to brown and green electricity supplier (A3) contribute 26% and 63%-65% in CO_2 reduction correspondingly. Our survey also shows that around 11% of households in Overijssel province already installed solar panels, this indicates households that already made an investment before 2016, are willing to switch to green supplier or save energy through changing their usage pattern. We observe that intensive social learning and diffusion of information (scenario FD) has more impact on A3 and A2.

4.3.2. Climate scenarios

To assess the impact of climate policies, an introduction of a carbon price in particular, we design the scenario SDC. Here the carbon price is introduced in the year 2017 and increases linearly to 25 euro per ton by 2030 on the grey (primary of coal) and brown (primary of natural gas) assuming 0.0009 ton CO_2 per kWh coal and 0.0003 ton CO_2 per kWh natural gas emission factors. Carbon pricing significantly encourages individual behavioural changes leading to additional 25% of CO_2 reduction in SDC compared to the SD scenario (Figure 4.6). This indicates that carbon pricing has a significant impact on switching to green suppliers since they are offering electricity at a lower price, and alternatively simply using less electricity to save energy costs. This is confirmed by the detailed breakdown of energy-related actions over time (Table 4.4).

In the scenario FDC we examine the effects of combining both behavioural heterogeneity, intensive social learning and climate policy on households energy decisions and consequently on their carbon footprint. Figure 6 shows that by combining the carbon price tax (25 Euro per ton) and households behavioural dynamics, we observe a significant reduction in CO_2 emissions of household electricity consumption by 55% in 2030 compared to the baseline.

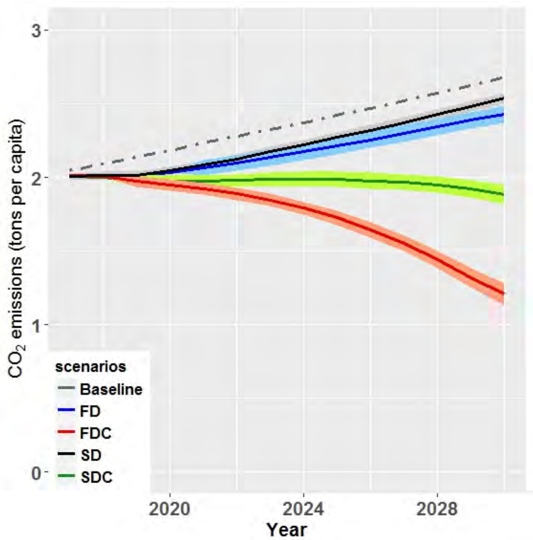


Figure 4.6: *Macro impact of heterogeneous households behavioural change combing (bottom-up) strategy and carbon price pressure (top-down) strategy on CO2 emissions over time. Combining behavioural-climate scenarios: combination of carbon price and slow and fast social dynamics (SDC, FDC) (2017-2030). The shaded bounds around the curves indicate the uncertainty intervals across 100 runs.*

As soon as the carbon price is introduced, the number of households' energy-related actions increases, leading to 1.3-2.1 times more CO_2 emission reduction per capita compared to behavioural scenarios (SD and FD) depending on the slow and fast social dynamics. In a world with slow social dynamics, the carbon price raises the number households choosing to switch from grey/brown electricity to the brown/green one (action A3) significantly to 3.5 times in compared to SD. Yet, as social interactions intensify, households who willing to invest (A1) take a lead and switching (A3) stand for the second and CO_2 emissions reduce up to 5.5 and 4.8 times respectively in compared to SD. At the same time the number of households who are interested in conservation and saving electricity by changing their habits and usage patterns (A2) increases 1.5 times as soon as the carbon price applies; it remains the same with combination of slow and fast social dynamics (SDC, FDC). This express that the top-down strategy –carbon pricing- notably activates the monetary part of individuals' decisions which lead to investment and switching.

Table 4.4: *Avoided CO_2 emissions (tons per capita) resulting from households energy-efficient actions, share of each action is reported in parenthesis; under behavioural and climate scenarios (SDC,FDC), 2030.*

Actions	*Scenarios*	
	SDC	***FDC***
A1: Investment	0.07 (18.4%)	**0.30 (17.4%)**
A2: Conservation	0.04 (9.6%)	0.16 (9.0%)
A3: Switching	**0.27 (72%)**	**1.27 (73.6%)**

4.3.3. Capturing non-linearities

Figure 4.7 illustrates that an increase in the intensity of social interactions across all 4 scenarios consistently leads to higher diffusion of actions A1-A3, implying that these behavioural changes deliver more CO_2 savings per capita under fast social learning rather than slow. At the same time, when fast social learning combined with top-down strategies –climate scenario (FDC)– it triggers significant changes in investment and switching, e.g. under FDC scenario investment and switching respectively leading to 4 and 5 times increase in comparison to SDC scenario. It quantitatively confirms that an effectiveness of a market-based climate policy is improved when accompanied by an information provision policy.

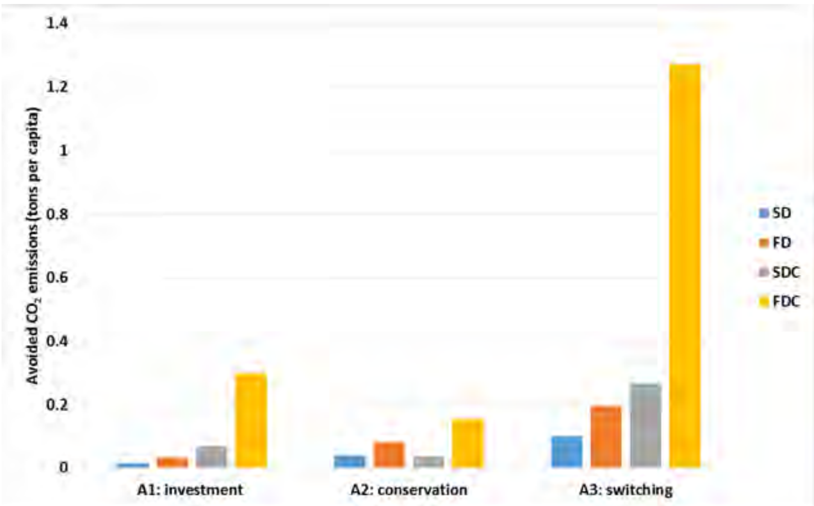


Figure 4.7: *Diffusion of households' actions under behavioural and climate scenarios*

The *BENCH-v.2* agent-based model gives us this opportunity to simulate complex and nonlinear behaviour that is intractable in equilibrium models. In figure 8, we reveal that while their combined effect is better than that of social dynamics or carbon price alone, the trend is non-linear. SD and SDC scenarios comparison demonstrates carbon price add more 25% CO_2 emission reduction. Examining SD and FD scenarios shows increasing social interactions alone reduces 4% CO_2 emission. However applying both carbon price and social interactions cuts down CO_2 emissions to 55% (21% more than rational models could estimate).

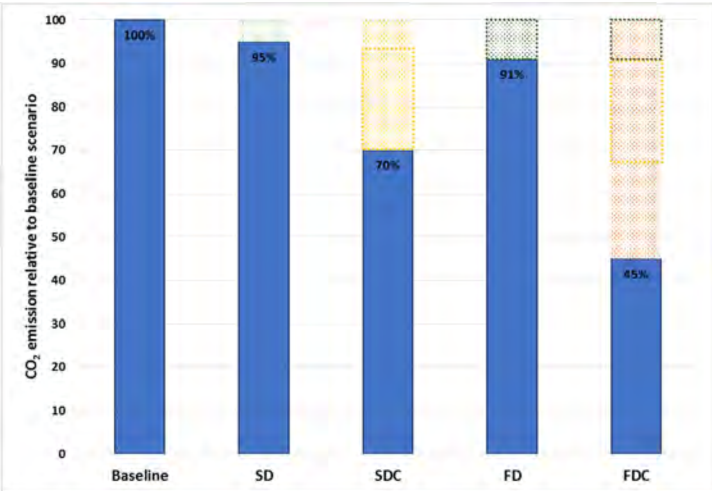


Figure 4.8: *The BENCH-v.2 agent-based model simulated complex and nonlinear behaviour that is intractable in equilibrium models. SD and SDC comparison shows carbon price reducing 25% CO_2 emissions (yellow box). FD shows increasing social interactions alone reduces 9% CO2 emissions (green box). However, applying both carbon price and social interactions cuts down CO_2 emissions by 55% (21% more than rational models could estimate).*

4.3.4. Sensitivity of emission reduction actions towards carbon price

Acknowledging the debate on the optimal level of a carbon tax, we performed a sensitivity analysis on the carbon price. We ran two additional scenarios – FDC10 and FDC50 – by varying the carbon price from 10 (FDC10) to 50 (FDC50) Euro per ton by 2030. Figure 5.9 illustrates the CO_2 emissions per capita resulting from individual behavioural changes A1-A3 assuming intensive social interactions under 3 carbon price values: 10

Euro/ton (FDC10), 25 Euro/ton (FDC25) and 50 Euro/ton (FDC50). According to Figure 8, the *BENCH-v.2* model is sensitive to the carbon price. As expected, the higher the carbon price the more CO_2 emission reduction is observed.

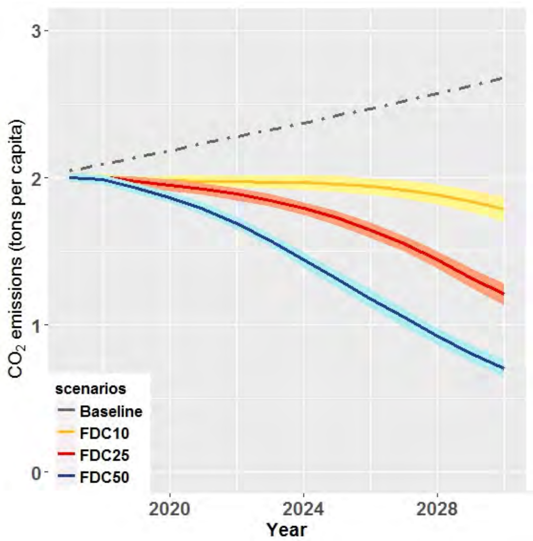


Figure 4.9: *Dynamics of CO2 emission reduction from individual behavioural changes (A1-A3) under different carbon price scenarios (€10, €25 and €50 per ton). The shaded bounds around the curves indicate the uncertainty intervals across 100 runs.*

4.4. Conclusions and policy implications

The potential of reducing CO_2 emissions through behavioural change becomes even more important in the light of the Paris agreement. To promote behavioural changes among households, a range of market-based as well as other behavioural nudging policies (e.g. information) could be used. Yet, many models assume that economic agents from a representative group(s), have perfect access to information and adapt instantly and rationally to a new situation. This paper focuses on estimating cumulative impacts of energy-related behavioural changes of individual households on CO_2 emissions by comparing behavioural and climate policy scenarios.

Here we apply the *BENCH-v.2* ABM to shed light on the effects of individual decisions in the complex climate-energy-economy system and explore the impact of socio-economic heterogeneity, social dynamics, and carbon pricing on their energy-related decisions over time in the Overijssel province of the Netherlands. While this study focuses on a relatively small geographical region, there are no principal barriers to upscale and apply the concept to a larger region, provided that sufficient statistical data are available (Niamir et al., 2018c).

The results indicate that accounting for demand side heterogeneity provides a better insight into possible transitions to a low-carbon economy and climate change mitigation. The model with household heterogeneity represented in socio-demographic, dwelling and behavioural factors, shows rich dynamics and provides more-realistic image of socio-economics by simulating economy through the social interactions of heterogeneous households. We analysed four end-user scenarios, which vary from the baseline scenario by introducing agent heterogeneity, intensity of social interactions among households (slow or fast) and lack or presence of carbon price (€10, €25 or €50 per ton). By comparing the behavioural and climate end-user scenarios, we estimate the relative impact of bottom-up drivers (social dynamics and learning on the diffusion of information) and top-down market policies (carbon price) on carbon emission reduction. The impact of household attributes heterogeneity and social dynamics brings 5%-9% CO_2 emission reduction by 2030. Adding carbon price cuts CO_2 emission down to 55% compared to the baseline scenario, which mimics the traditional economic setup of a rational representative fully-informed household who makes the optimal decision.

It should be noted that in this research we only focus on the demand side of the electricity market and calculated CO_2 emissions caused by residential demand. Future work could focus on integrating this behaviourally rich demand side Modelling with dynamics of the electricity production side in the market with detailed modelling of various energy sources.

The results imply that the design of climate mitigation policies aiming at behavioural changes should go beyond making the energy-related alternatives more attractive financially. In a transition to low-carbon economy, individuals become more than just consumers. In order to facilitate this transition, the broader view on social environment, cultural practices, public knowledge, producers technologies and services, and the facilities used by consumers are needed to design implementable and politically feasible policy options (Bressers and Ligteringen, 2007). Accordingly, the policy mix should also aim at encouraging and facilitating social interactions between individuals (households) and promoting and diffusing information that they need. Such accompanying information and value based policy instruments have the potential to greatly contribute to the effectiveness of conventional price-based policies. Therefore, the various financial, social and other instruments in the policy mix should be designed as a coherent set to reinforce each other, optimizing the joint effectiveness.

Chapter 5:

ECONOMY-WIDE IMPACTS OF CLIMATE CHANGE MITIGATION BEHAVIOUR AMONG HETEROGENEOUS AGENTS: LINKING AGENT-BASED AND COMPUTABLE GENERAL EQUILIBRIUM MODELS

Niamir, L., Ivanova, O., Filatova, T.

Global Environmental Change (Under review)

Parts of this chapter also appeared in:

- Niamir, L., et al. (2018). Tracing Macroeconomic Impacts of Individual Behavioural Changes through Model Integration. IFAC-PapersOnLine 51 (5), 96-101.
- Niamir, L., et al. (2015). Linking agent-based energy market with computable general equilibrium model: an integrated approach to climate-economy-energy system. WEHIA, 21-23 May, Sophia Antipolis, France.
- EU FP7 COMPLEX. Reports D5.3 and D5.4

Abstract

Households are responsible for a major share of global greenhouse emissions. Academic and policy discourses highlight behavioural changes among households as an essential strategy for combating climate change. However, the formal models used to assess the impacts of such policies face limitations in tracing the cumulative impacts of individual adaptive behaviour of heterogeneous households. This paper suggests a systematic way to scale up heterogeneous individual energy behavioural changes to trace their macroeconomic cross-sectoral impacts. To achieve this goal, we combine the strengths of macroeconomic computable general equilibrium models and microsimulation agent-based models. We illustrate the integration process of these two opposed modelling approaches by linking data-rich macro and micro models. Following a three-step approach, we investigate the dynamics of cumulative impacts of changes in individual energy use under three behaviour scenarios. The findings of this softly-linked model indicate that the education and age structure of different EU regions leads to an unequal distribution of benefits of the green economy transition between pioneering and lagging regions. Heterogeneity in individual sociodemographics (e.g. education and age), structural characteristics (e.g. type and size of dwellings), behavioural and social traits, and spatial characteristics (e.g. urban vs. rural) and social interactions amplify these differences, causing nonlinearities in market dynamics..

5.1. Introduction

Energy consumption is the primary culprit behind anthropogenic global warming. Humanity's demand for energy is satisfied by consuming fossil fuels as well as renewable energy sources, leading to varied greenhouse gas emission (GHGs) footprints. Households are responsible for 70% of global GHGs (Hertwich and Peters, 2009). In Europe, one quarter of direct total energy consumption and GHGs comes from households[*]. Academic and policy discourses highlight behavioural changes among households as an essential strategy for reducing GHG emissions and combating climate change (Dietz et al., 2013; Doppelt and Markowitz, 2009; Faber et al., 2012; McKinsey, 2009). An individual's decision-making is, however, known to deviate from rational and perfectly informed optimization process, calling for a thorough understanding of behavioural aspects (Abrahamse and Steg, 2011; Bamberg et al., 2007; Bamberg et al., 2015; Poortinga et al., 2004; Raaij, 2017; Stern et al., 2016a). Gadenne et al. (2011) study the influence of households' environmental beliefs and attitudes on energy behaviours. They find that people pay more attention to environmental issues nowadays, following intensive efforts to promote a green consumer lifestyle. Beliefs and lifestyle preferences define personal choices, which could reduce an individual's carbon footprint. Investing in insulation, renewable energy sources (e.g. installing PVs) and in energy-efficient appliances are the most common decisions households take to reduce GHGs[†]. Given the impact household energy consumption has on emissions and an emerging shift in social norms, individual behavioural change has become central in the discourse on climate change mitigation (Creutzig et al., 2018b; Rai and Henry, 2016; Stern et al., 2016a).

[*] https://climatepolicyinfohub.eu/node/71/pdf

[†] https://www.carbonfootprint.com/minimisecfp.html

Policy-makers and stakeholders rely on decision support tools to assess future changes in energy markets and the economy as a whole. Macroeconomic Computable General Equilibrium (CGE) models serve as standard tools for quantitative policy assessments in climate change mitigation (Babatunde et al., 2017; Fujimori et al., 2017; IPCC, 2014a; JRC, 2014; Rive et al., 2006; Vandyck et al., 2016). Macroeconomic models focus on investments and consumption patterns in different sectors associated with GHGs reduction policies by simulating markets for factors of production and foreign exchange, with equations that specify supply and demand behaviour. CGE models are strong in tracing cross-sectoral impacts and linking to readily-available datasets. These models are able to generate new equilibria by introducing a policy shock. Carbon taxes, emission reduction targets, emission trading, renewable energy, energy efficiency, and carbon capture and storage are the main research questions addressed by sophisticated CGE models for energy policy assesments (Babatunde et al., 2017). However, these macroeconomic and CGE models assume a rational representative agent who makes optimal decisions under budget constraints, perfect information and competitive markets (Babatunde et al., 2017; Farmer et al., 2015; Stern, 2016). Morevoer, while relying on quantity and price adjustments via a market equilibrium, CGEs implicitly reflect past behaviour. Their parameters are partly calibrated and the rest of their driving equations are econometrically estimated using time-series data. Therefore, macroeconomic models are suitable for testing the economic effects of GHGs reduction policies for short-horizons (IPCC, 2014a), making it difficult to integrate behavioural changes. Hence, their validity and capacity to provide unbiased climate mitigation policy advice is debated (Creutzig et al., 2018a; Farmer and Foley, 2009; Farmer et al., 2015; Isley et al., 2015; Stern, 2016).

In contrast to this macroeconomic "top-down" approach, "bottom-up" micro-simualtion models focus on behaviorally- and technologicaly-rich representation of energy demand and supply, out-of-equilibrium dynamics, social interactions and learning (Bhattacharyya, 2011; Farmer et al., 2015; Hunt and Evans, 2009). Prominent among bottom-up approaches is agent-based modelling. Agent-based models (ABMs) compliment macro-economic models by accommodating heterogeneity, adaptive behaviour and interactions, bounded rationality, and imperfect information. These features make ABM a popular method in energy studies (Anatolitis and Welisch, 2017; Isley et al., 2015; Lamperti et al., 2018; Rai and Henry, 2016; Rai and Robinson, 2015; Stern et al., 2016a; Stern et al., 2016b). However, their empirical use for climate mitigation policy support is limited due to the high-data intensity required to specify individual behavioural rules. Moreover, there are difficulties with the generalization and scaling up of ABM results (Humphreys and Imbert, 2012; Lamperti et al., 2018), making the assessment of economy-wide impacts difficult.

Exploring synergies by combining the two approaches has long been a temptation in science (Krook-Riekkola et al., 2017; Melnikov et al., 2017; Parris, 2005; Safarzyńska et al., 2013; Smajgl et al., 2009). Linking ABMs and CGE models could ameliorate their weaknesses, covering the trade-offs between complexity and realism. CGE models are strong in simulating cross-sectoral impacts in a national and regional economy, while ABMs zoom into a specific sector such as residential energy, where behavioural heterogeneity is known to be important (Farmer and Foley, 2009; Rai and Henry, 2016; Smajgl et al., 2009; Stern, 2016). Several scholars have attempted to integrate ABM and CGE models. Safarzyńska et al. (2013) propose an elegant way to integrate the evolutionary dynamics of ABMs into a CGE model, but leave it at the conceptual level without an implementation. Smajgl et al. (2009) employ a ABM and CGE model for integrated policy impact assessment. Meanwhile, Krook-Riekkola et al. (2017) highlight the importance of a soft-linking approach. They propose and discuss the soft-linking of CGE and partial equilibrium models when assessing national energy policies. They develop a transparent process to transfer simulation results between model. Melnikov et al. (2017) explore the mitigation effects on household energy consumption by using a recursive-dynamic and forward-looking downscaling method for the CGE model using a survey data. However, both approaches still miss behaviourally-rich representation of individual choices and social interactions. Moreover, an empirical example of resolving the key methodological differences between ABM and CGE modelling while aligning with data is missing. The current paper addresses this methodological gap by demonstrating how the aggregated impacts of household energy behaviour changes delivered by an empirical ABM could be further scaled up and connected to the macroeconomic dynamics of a CGE model. The objective of this paper is twofold: (1) to present a systematic way to link ABM and CGE models targeting individuals' heterogeneity and behavioural changes; and (2) to study the impacts of climate change mitigation behaviour across scales, from individuals to the EU.

5.2. Methodology

CGE models are a popular instrument for ex-ante policy analysis and are widely used by governments, the European Commission and academia in their policy studies. CGE models rely on advancements in micro-economic theory that represent the aggregate behaviour of main economic agents (household, firms and governments) and interactions between them via supply-chain and trade links. CGE models are well-suited for the analysis of various financial policies such as taxes and subsidies (for example CO_2 tax) and much less for analysing behavioural changes. To trace macro level effects, CGE models aggregate preferences of various actors by assuming a representative rational fully-informed agent that is capable of making the optimal choice. Behavioural changes, including behavioural climate change mitigation actions, for example driven by increased level of knowledge about climate change in society and shifts in preferences, are difficult to integrate. To be able to analyse the macro-economic and sectoral impacts of such behavioural changes, CGE models rely on complimentary modelling tools such as AMBs. The current paper employs the strengths of ABMs to capture and aggregate behavioural changes, social interactions and learning, and the strength of CGE models to trace cross-sectoral impacts and indirect effects. The scientific challenge is in aligning two types of models that differ on a number of key assumptions: (1) CGE models work with a representative agent (group) while ABMs assume heterogeneity in attributes and behaviour; (2) agents in CGE are assumed to be fully rational and have adaptive expectations while ABMs proliferate in tackling research problems where bounded rationality is relevant; (3) CGE models are designed to resolve via the assumption of a unique equilibrium while ABMs are designed to study out-of-equilibrium dynamics and an evolution across equilibria.

In what follows, we outline the main principles of each modelling approach and their core processes that are most relevant for the purpose of this article (Sections 5.2.1 and 5.2.2). Our ABM and CGE models are aligned conceptually and in terms of data flows to ensure a smooth integration. The flow of information in our modelling exercise is from the ABM model for two individual EU regions to the CGE model via upscaling the ABM results to the rest of the EU NUTS2 regions. We do not consider any direct feedback from the CGE model and ABM models at this moment because of the non-financial nature of the behavioural changes in ABM. The CGE to ABM link is indirect, by introducing a scenario of EU income growth rates. Aggregated impacts of individual behavioural changes are estimated for a range of behavioural scenarios (Section 5.2.3). Behavioural changes in ABM are influenced by various non-monetary factors such as knowledge and awareness that depend upon the education level and gender of individuals. Introducing a direct link from CGE to ABM and allowing for mutual feedback is a promising direction of future work, that, among other benefits, will enable the evaluation effects of joint price-based and information climate mitigation policies at multiple scales.

General Equilibrium (CGE) models is a popular instrument for ex-ante policy analysis and are widely used by governments, European Commission and the academia in their policy studies. CGE models rely on advancements in micro-economic theory that represent the aggregate behaviour of main economic agents (household, firms and governments) and interactions between them via supply-chain and trade links. CGE models are well-suited for the analysis of various financial policies such as taxes and subsidies (for example CO2 tax) and much less for analysing behavioural changes. To trace macro level effects, CGE models aggregate preferences of various actors by assuming a representative rational fully-informed agent that is capable of making the optimal choice. Behavioural changes, including behavioural climate change mitigation actions, for example driven by increased level of knowledge about for climate change in the society and shifts in preferences, are difficult to integrate. To be able to analyse the macro-economic and sectoral impacts of such behavioural changes CGE models rely on complimentary modelling tools such as Agent-based Models (AMBs). The current paper employs the strengths of ABMs to capture and aggregate behavioural changes, social interactions and learning, and on the strength of CGE models to trace cross-sectoral impacts and indirect effects. The scientific challenge is in aligning two types of models that differ on a number of key assumptions: (1) CGE models work with a representative agent (group) while ABMs assume heterogeneity in attributes and behaviour; (2) agents in CGE are assumed to be fully rational and have adaptive expectations while ABMs proliferate in tackling research problems where bounded rationality is relevant; (3) CGE models are designed to resolve via assuming a unique equilibrium while ABMs are designed to study out-of-equilibrium dynamics and an evolution across equilibria.

In what follows we outline the main principles of each modelling approach and their core processes that are most relevant for the purpose of this article (Sections 5.2.1 and 5.2.2). Our ABM and CGE models are aligned conceptually and in terms of data flows to assure a smooth integration. The flow of information in our modelling exercise is from ABM model for two individual EU regions to the CGE model via upscaling the ABM results to the rest of EU NUTS2 regions. We do not consider any direct feedbacks from CGE model and ABM models at this moment because of the non-financial nature of the behavioural changes in ABM. The CGE to ABM link is indirect by introducing a scenario of EU income growth rates. Aggregated impacts of individual behavioural changes are estimated for a range of behavioural scenarios (Section 5.2.3). Behavioural changes in ABM are influenced by various non-monetary factors such as knowledge and awareness that depend upon education level and gender of individuals. Introducing a direct link from CGE to ABM and allowing for mutual feedbacks is a promising direction of future work, that, among others, will permit to evaluate effects of joint price-based and information climate mitigation policies at multiple scales.

5.2.1. Agent-based model (BENCH model)

General description

The *BENCH* ABM (Niamir et al., 2018b; Niamir et al., 2018d) is developed to study shifts in residential energy use and corresponding emissions driven by behavioural changes among individuals. Households in *BENCH* are heterogeneous in socio-demographic characteristics (e.g. income, age, education), dwelling characteristics (e.g. type, size, age), energy consumption patterns (e.g. electricity and gas consumption, energy provider), and behavioural factors (e.g. awareness, personal norms, social norms). This ABM is spatially explicit, with behavioural rules of agents calibrated based on the survey data for two EU NUTS2 regions: Navarre, Spain and Overijssel, The Netherlands (Niamir et al., 2018d). Compared to its previous versions, *BENCH-v.3* presented in this article has been further developed to investigate the role of individual energy behavioural changes in a low-carbon economy transition. Namely, agents' utility function is modified to align empirically-grounded energy decisions from the households' survey with macroeconomic dynamics in our data-driven CGE model. This enables us to systematically upscale individual differences in decisions and behavioural traits to national and EU levels. In particular, *BENCHv.3* focuses on energy investments that households may decide to undertake: significant investments in house insulation (I1) or solar panels (I2), and more modest investments in energy-efficient appliances (I3).

Main processes in the model

Following the Theory of Planned Behaviour and Norm Activation Theory from psychology, we assume that bounded rational households in *BENCH-v.3* make decisions following a number of cognitive stages: knowledge activation, motivation and consideration (Figure 1). Households differ in knowledge and awareness about climate, environment and energy issues (*k, cee.aw, ed.aw*), personal (pn_i) and social norms (sn_i), and perceived behavioural controls (pbc_i). These behavioural factors are initiated in *BENCH-v.3* based on the original survey data (Niamir et al. (2018b); Niamir et al. (2018d). High level of knowledge and awareness (i.e. mean *k, cee.aw, ed.aw* is above the empirical threshold) triggers a "*feeling guilt*" among agents. Such individuals proceed to evaluate the motivational factors: personal and social norms (pn_i , sn_i) for each action (I1-I3). If individuals are highly motivated and "*feel responsible*", the perceived behaviour controls[*] (pbc_i), and the

[*] Own perception of their ability to perform an action or change behavior

dwelling ownership status (owner or renter) are evaluated to assess "*intentions*". Individuals with a high level of intention proceed to estimate utilities, which are formulated as a discrete choice problem here. Household agents follow these stages for each action: when deciding whether to invest in insulation, solar panels or energy-efficient appliances.

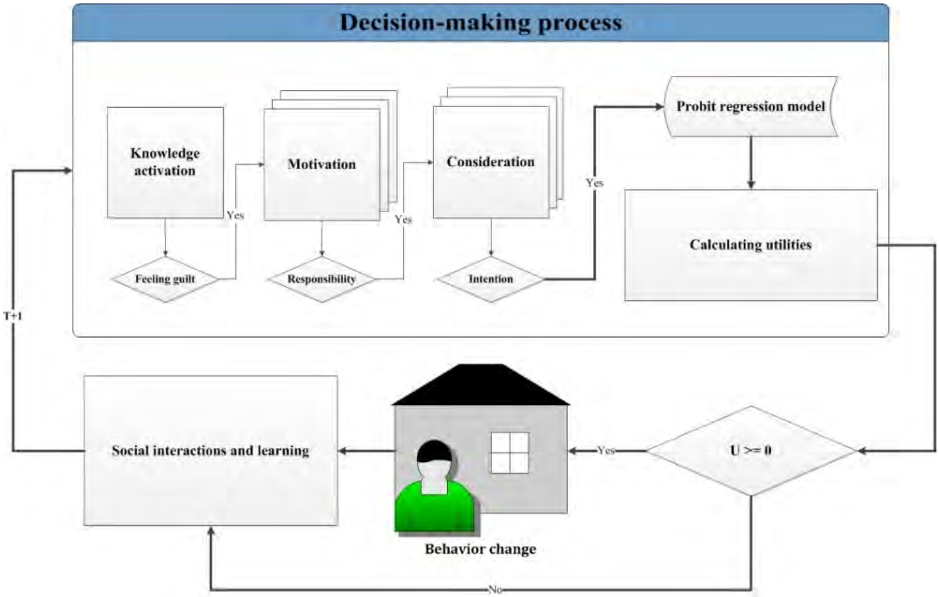


***Figure 5.1**: Cognitive process behind individual behavioural changes (e.g. energy-efficient investments): BENCH-v.3 ABM structure.*

Households in *BENCH v.3* make choices based on the indirect utility function (Eq.1). As the inverse of the expenditure function when prices are constant, it reflects individual preferences for different energy actions under budget constraints.

$$V_{ij} = \sum x_{ij}\beta_i + \varepsilon_{ij} \tag{1}$$

The utility of individual j associated with choice i (V_{ij}) is calculated based on the vector of explanatory observed and latent variables (x_{ij}) – including socio-economic characteristics of the individuals, dwelling characteristics, and financial and ownership situation, as well as behavioural factors – and the parameter vector (β_i) estimated using a probit regression (Niamir et al. (2018b); Niamir et al. (2018d). Finally, ε_{ij} is the vector of error terms. An individual chooses a particular sub-action (i) – energy investment, conservation or switching – when their utility is non-negative:

(2)

$$If\ V_{ij} \geq 0 \quad (A_{ij} = True\ \ else\ A_{ij} = False)$$

Social interactions are proven to influence individual choices (Bamberg et al., 2007; Bamberg et al., 2015; Nyborg et al., 2016; Rai and Henry, 2016). In *BENCH-v.3* , agents exchange information following a simple opinion dynamics model (Moussaid et al., 2015). When a neighbour takes an action (I1-I3), it may alter knowledge, awareness and the motivational factors regarding energy choices of others in this peer group. Namely, individuals compare own behavioural factors (k, $cee.aw$, $ed.aw$, pn_i, sn_i, pbc_i) with those of their closest neighbours, and gradually adjust them (Eq.3). We run various scenarios of this social learning (see 2.3).

(3)

$$X = \{k_j, cee.aw_j, ed.aw_j, pn_{ij}, sn_{ij}, pbc_{ij}\} \quad ;$$

$$If\ Max\ (mean\ (X_j^t), median\ (X_j^t)) \geq\ X_{j^*}^t \quad (X_{j^*}^{t+1} =\ X_{j^*}^t + 0.02 \cdot X_{j^*}^t)$$

Data

The BENCH model is calibrated based on an empirical dataset. We designed and conducted the survey in two provinces in Europe for the purpose of this research. In 2016, 1035 households in the Overijssel province, the Netherlands, and 755 households in the Navarre province, Spain, filled out our online questionnaire (Niamir et al. (2018b); Niamir et al. (2018d). Appendix A provides more detail on our case studies.

Outputs

The agent-based *BENCH.v3* model tracks the individual and cumulative impacts of three energy behavioural changes (investments on insulation, PVs installation and energy-efficient appliances) among heterogeneous individuals in the Overijssel and Navarre provinces over 34 years (2016-2050). We report the *number of individuals pursuing a particular action (I1-I3)*, the cumulative *electricity* and *gas consumption*, and *saved carbon emissions*. Given the stochastic nature of ABMs, we perform multiple (N=100) repetitive runs of each simulation experiment (Lee et al., 2015).

5.2.2. Spatial CGE mode (EU-EMS model)

General description

EU-EMS is a spatial computable general equilibrium (SCGE) model developed by PBL Netherlands Environmental Assessment Agency. The sectoral and geographical dimensions of the model are flexible and can be adjusted to the needs of a specific policy or research question. The model is used for policy impact assessment and provides sector-, region- and time-specific model-based support to Dutch and EU policy makers on structural reforms, growth, innovation, human capital and infrastructure policies. The current version of EU-EMS covers 276 NUTS2 regions of the EU28 Member

States and each regional economy is disaggregated into 63 NACE Rev. 2 economic sectors[*]. Goods and services are consumed by households, government and firms, and are produced in markets that can be perfectly or imperfectly competitive. Spatial interactions between regions are captured through trade of goods and services, factor mobility and knowledge spill-overs. This makes EU-EMS particularly well suited for analysing policies related to human capital, transport infrastructure, R&I and innovation.

In the current application of the model, we have aggregated the economic sectors to the following six large groups, following the Eurostat classification of the economic sectors according to their R&D intensity: (1) Traditional, (2) Low-tech industry, (3) Medium-tech industry, (4) High-tech industry, (5) Knowledge intensive services and (6) Other services.

Main processes of the model

Following the tradition of comprehensive empirical CGE models, EU-EMS uses large datasets of real economic data in combination with complex computational algorithms to assess how the economy reacts to changes in governmental policy, technology, availability of resources and other external macro-economic factors. The EU-EMS model consists of (a) the system of non-linear equations, which describes the behaviour of various economic actors, and (b) a very detailed database of economic, trade, environmental and physical data. The core part of the model database is the Social Accounting Matrix, which represents in a consistent way all annual economic transactions.

EU-EMS accounts for the (a) feedback between price and demand/supply quantities, and (b) interactions between economic agents at the macro and sectorial level. Therefore, it gives the economic relations between all

[*] https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF

industry sectors via their intermediate use. The EU-EMS model is a dynamic, recursive over time model, involving dynamics of capital accumulation and technology progress, stock and flow relationships and adaptive expectations.

The model equations are neo-classical in spirit, assuming cost-minimizing behaviour by producers, average-cost pricing and household demands based on optimizing behaviour (see Appendix B for details). The CGE model database consists of tables of transaction values and elasticities: dimensionless parameters that capture behavioural response. The database is presented as a Social Accounting Matrix, which covers an entire national economy, and distinguishes a number of sectors, commodities, primary factors and types of households. As a classical CGE model, EU-EMS represents the behaviour of the whole population group or of the whole industrial sector as the behaviour of one single aggregate agent. It is further assumed that the behaviour of each such aggregate agent is driven by certain optimization criteria such as maximization of utility or minimization of costs. Appendix B provides detailed representation of the EU-EMS model and its main equations.

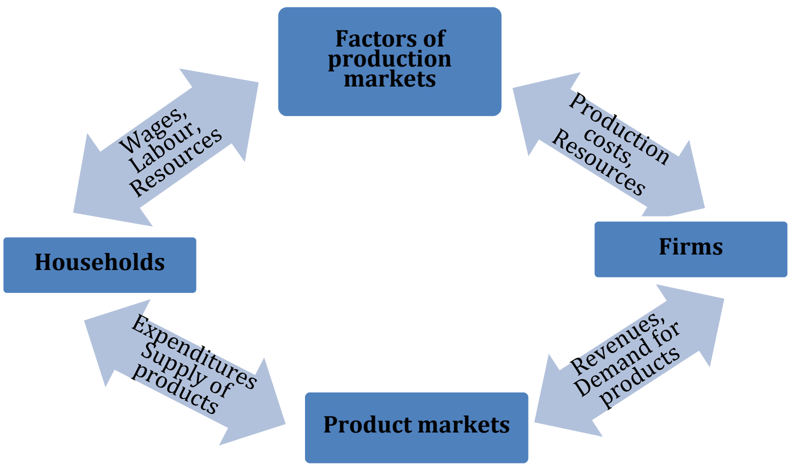


Figure 5.2*: Circular economic flow in the CGE EU-EMS model*

Data

The The EU-EMS model uses a comprehensive database that has detailed regional dimensionality for the EU28 countries and includes them as consisting of 276 NUTS2 regions. The database[*] of the model has been constructed by PBL using the combination of national, European and international data sources and represents a detailed regional level (NUTS2 for EU28 plus 34 non-EU countries) multi-regional input-output (MRIO) table for the world. The main datasets used for the construction of this MRIO include the 2013 OECD database, BACI trade data, Eurostat regional statistics, and national Supply and Use tables, as well as the detailed regional level transport database of DG MOVE called ETIS-Plus[†]. The later dataset allows us to estimate the inter-regional trade flows at the level of NUTS2 regions that are currently not available from official statistical sources. The aggregated groups of the sectors can be directly linked to the econometric analysis and estimations that have been done for Total Factor Productivity (TFP) projections using the EU-KLEMS database[‡].

Outputs

The EU-EMS model produces detailed dynamics of regional GDP, production and value added by region and by economic sector, interregional trade flows by the type of commodity, electricity and gas consumption per region and sector, employment by regional and economic sector, household income and consumption, and governmental revenues and spending. For the purpose of this article we limit the presentation of the main CGE output to

[*] http://themasites.pbl.nl/winnaars-verliezers-regionale-concurrentie/

[†] http://viewer.etisplus.net/

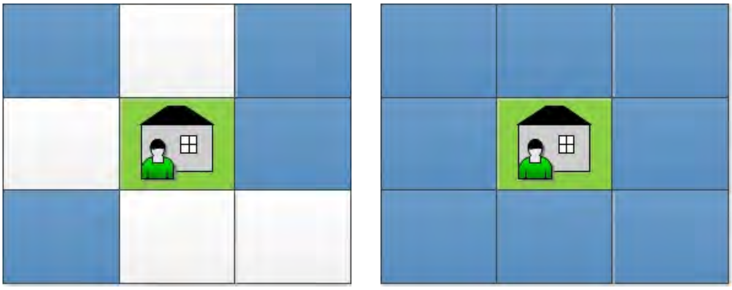
[‡] http://www.euklems.net/

Gross Domestic Product (GDP), percentage change in the electricity consumption per NUTS2 region, country and the entire EU.

5.2.3. Scenarios

We run three behavioural scenarios in *BENCH-v.3* ABM differentiating between the intensity of social interactions and the speed of learning. Households heterogeneous in income, electricity and gas consumption and dwelling conditions follow a cognitive process to decide whether to pursue any energy investment. The awareness (*k, cee.aw, ed.aw*) and motivation (pn_i , $sn_{i,}$, pbc_i) of agents are updated as soon as at least one household in the neighbourhood pursues an action (I1-I3). Based on the scope of the neighbourhood, this social learning may occur at either a slow or fast pace. Under slow dynamics (*Baseline scenario*), an individual in an active neighbourhood interacts with a maximum of four neighbours (Fig. 3.a). Under fast dynamics (*scenario FD*), all eight individuals in an active neighbourhood exchange opinions and learn from each other (Fig. 3.b). Scenario *FD* indicates the upper limit of the bottom-up diffusion of pro-environmental social norms driven by households alone without any policy support. In the *Baseline* and *FD* scenarios, individuals with the value of their behavioural attributes – $k_j, cee.aw_j, ed.aw_j, pn_{ij}, sn_{ij}, pbc_{ij}$ – lower than that of their neighbours adjust by increasing the value of by 2% (Eq.3).

Informative dynamic (*scenario ID*) assumes an information policy – e.g. social advertising and the promotion of pro-environmental behaviour – that raises the level of knowledge and motivation in the entire population. Hence, at initialization all households agents start with 2% higher values on behavioural attributes, before engaging in any social learning. The *ID scenario* highlights the importance of information diffusion and promoting strategies focused on behavioural climate mitigation. It assumes that all individuals do update their knowledge and motivation when the information policy applies. The processes of shaping an information campaign and of its diffusion (immediate or with delay for certain parts of the population) is beyond the scope of this paper. Scenario *ID* assumes that all agents update their knowledge when an information campaign is in action, and illustrates how a public policy could support the bottom-up process by amplifying pro-environmental social norms.



(a) Slow dynamics: random 4 households are affected and engage in social learning

(b) Fast dynamics: all households in the neighbourhood are affected and engage in social learning

Figure 5.3*: Social dynamics and learning in a neighbourhood where an individual undertook an action at time t.*

In addition to the three behavioural scenarios in the *BENCH.v3* ABM, the EU-EMS CGE model includes the demographic projections from Eurostat until 2050, and TFP projections by economic sector based on our own econometric analysis. Hence, the macroeconomic and demographic scenarios are combined with the slow/fast/informative dynamics scenarios about micro-level behaviour with respect to electricity and gas use by heterogeneous households.

5.2.4. Upscaling individual behavioural changes: linking ABM and CGE

ABM and CGE models each have their own assumptions, strength and weaknesses. We attempt to overcome the latter by linking the two models. To pursue this aim in a systematic manner, we take a step-wise approach to bridge the ABM with the CGE model (Fig.5.4.).

Step 1: We run the ABM model for two individual NUTS2 regions in the Netherlands and Spain. Our ABM calculates the extent of behavioural changes among heterogeneous household agents who evolve through a cognitive process (knowledge activation, motivation and consideration, Fig.1) before reaching a more rational stage where the discrete-choice utility maximization is activated. The main outcomes of the ABM model that are of use to the CGE model include the relative changes in electricity and gas use as well as the total investments made by various types of individuals who decide to undertake actions I1-I3. The CGE model EU-EMS, however, operates at the level of all 276 EU28 NUTS2 regions, and needs to use the regional changes in energy consumption and investments of the representative households as an input. Hence, the behavioural patterns emerging at the Overijssel and Navarre provinces for different households need to be scaled not only up to the national level, but up to the entire EU.

Step 2: We take an intermediate step to derive the changes in investments, gas and electricity consumption across households of different age and education levels for all 276 EU28 NUTS2 regions based on the outcomes of two regional ABMs. To do this, we define behavioural patterns for a group of households in the Dutch and Spanish regional ABMs separately, aggregated by age and education level. Following Eurostat classification, we work with 12 age-education groups (see Table 5.A.2, Appendix A). For each of the 12 groups, we estimate a number of households pursuing an action (I1-I3) and calculate the corresponding average gas and electricity savings and investments. The behavioural patterns –awareness, motivations, intentions and likely actions– across 12 groups differ between the two countries in our survey sample, and so they do in the regional ABMs. To utilize the information regarding the cultural aspects of each region in the best way, we create the mapping between NUTS2 regions of the EU28 with the two ABM regions according to their perceived cultural distance (Kaasa et al., 2016). The Dutch region is associated in the mapping with the Scandinavian and Western European regions, whereas the Spanish region is associated with the Eastern European and Mediterranean regions. Ideally, we would use survey behavioural data for each of the EU28 states. In the absence of such data, this approach is the best approximation we could find to account for cultural differences using the available data at hand.

Since behavioural changes vary primarily among households with different age and education levels, the changes in these characteristics over time are crucial. Hence, we employ demographic projections for the period until 2050. The only regional NUTS2 level projections that have been done for the EU28 are EUROPOP2008[*] projections of Eurostat. Population projections of Eurostat provide information about the development of the population until 2050, detailed by age and gender groups. Furthermore, Eurostat population projections at NUTS2 level are combined with IIASA Global Education Trends (GET) scenario projections[†] related to the share of high, medium and low-educated persons in each EU country. This allows us to construct population projections by age and education level for the period 2020-2050 for each NUTS2 region of the EU28. These NUTS2-level population projections till 2050 match with the scaled-up mapping of behavioural patterns of 12 groups in our ABM. Hence, now age and

[*] https://ec.europa.eu/eurostat/documents/3433488/5564440/KS-SF-10-001-EN.PDF/d5b8bf54-6979-4834-998a-f7d1a61aa82d

[†] http://www.iiasa.ac.at/web/home/research/researchPrograms/WorldPopulation/Projections_2014.html

education information can be linked with the emerging behavioural patterns of the agent-based BENCH v.3 model to create NUTS2 specific – that is, corresponding to the population structure of that region – inputs into the spatial EU-EMS CGE model.

Step 3: Finally, we use the predicted population structure by age and education level for the period 2020-2050 to calculate aggregated changes in the residential use of gas and electricity for each NUTS2 regions of EU28 on the basis of calculated averages for each of the 12 individual groups. The EU-EMS CGE model estimates the cross-sectoral impacts of these shifts in the aggregated residential energy demand that impacts GDP projects. The linked ABM-CGE model quantifies the cumulative impacts of behavioural changes among heterogeneous households at the level of 276 EU28 NUTS2 regions. This allows us to understand the impacts of various behavioural scenarios within the CGE framework, including distributional effects across these EU regions. An important direction of future work would be to develop direct two-way linkages between the two models, with the CGE-generated GDP projections feeding back into the ABM.

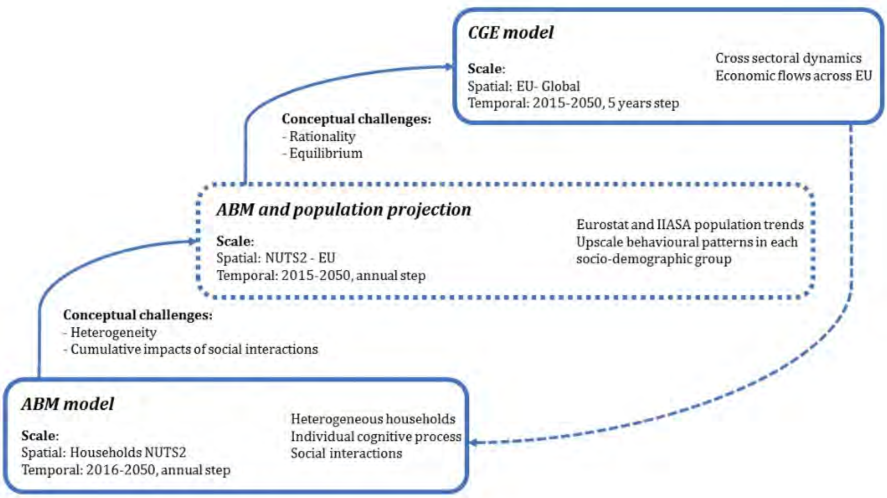


***Figure 5.4**: Upscaling individuals behavioural change via linking ABM and CGE models.*

This step-wise approach to linking the ABM and CGE models allows us to address the key methodological challenges:

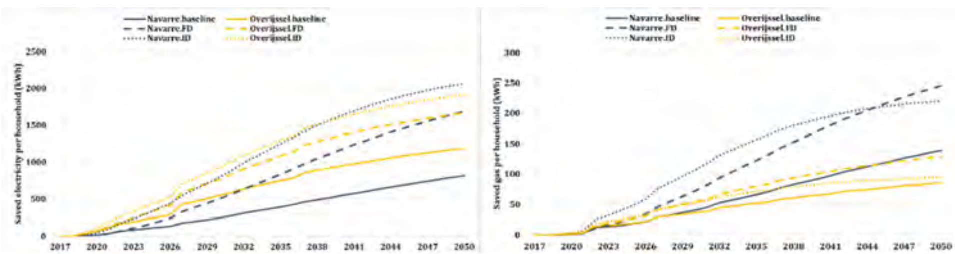
- **From representative to heterogeneous agents**: Heterogeneous households in the ABM are matched with representative households in the CGE model. Aggregation occurs along the two dimensions that impact relevant behavioural changes among households most: age and education levels. This is done using detailed information about the structure of the population by age and education in each NUTS2 region for the period 2020-2050 while keeping behaviour heterogeneous across the 12 groups.
- **From perfect to bounded rationality**: Agents in our ABM are boundedly rational due to the presence of behaviour factors that precede discrete choice utility estimate: subjective knowledge and awareness, motivation, and intention to consider a change in behaviour, which are all prone to social influence. The use of the ABM allows us to assess the impacts of pure behavioural changes in the CGE model and calculate their broader economic impacts. The rest of the economy in the CGE model – e.g. households' decisions on a labour market, decisions of firms, clearing of the markets – still operates in line with the rationality principles, allowing for the coherent treatment of macro-economic processes in the EU-EMS CGE.
- **From an equilibrium to adaptive dynamics with social learning**: The CGE model is based on assumptions of market equilibrium and interlinkages between different agents, sectors and markets in the economy. The ABM treats agents' decisions as a cognitive process in the presence of social interactions and fast/slow/informative learning.

5. Results

5.3.1. From behavioural patterns in survey data to cumulative impacts in two provinces (Step 1)

Firstly, we run the BENCH.v3 ABM for two EU provinces (Overijssel and Navarre) under three behavioural scenarios (*Baseline, FD* and *ID*). We report the regional impacts of the energy behaviour choices of heterogeneous households: the diffusion of each of the three types of behavioural actions among heterogeneous households over time, the changes in electricity and gas consumption, saved CO_2 emissions, and the amount of investment.

Figure 5.5 illustrates the dynamics of electricity and gas saving in the two EU provinces as a result of households' energy investments. The general trend is as expected: faster learning boosted by an information campaign leads to more investments in solar panels (I2) and in appliances (I3), and consequently to higher electricity savings in both provinces. Intensive social learning boosts electricity savings by 40% and 100% in Overijssel and Navarre (*FD* vs *Baseline*, Fig.5.5.a and Table 5.1). In addition, electricity savings increase by 14% and 22% in two provinces if pro-environmental awareness is raised through an information policy (*ID* vs *FD*, Fig.5.5.a and Table 5.1).



(a) electricity (b) gas

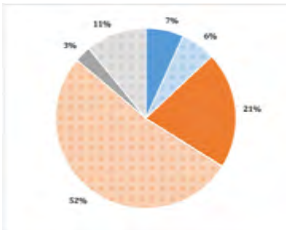
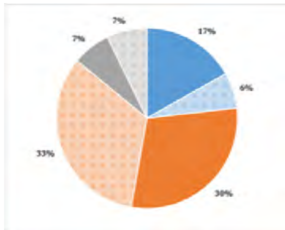
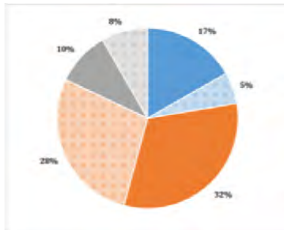
Figure 5.5: *Saved energy (kWh) per households as a result of investments (I1-I3) under three behavioural scenarios in two EU provinces over 34 years (2017-2050). Source: BENCH-v.3*

However, it does not hold for investments in insulation (I1) and corresponding gas savings. Informative strategy (*ID*) has a mixed impact on insulation investments in Navarre (crossing of *FD* and *ID* curves in Fig.5.5.b) and the opposite effect in Overijssel (*ID* delivers 26% lower gas savings compared to *FD*, Fig.5.5.b). The difference between provinces may be driven by different climate and institutional conditions and the gas prices in the two countries. In addition, comparing *FD and ID* scenarios shows that an information policy and social interactions among neighbours impact households' insulation decisions in a non-linear way.

Table 5.1 shows the amount of CO_2 emission savings that households' energy behaviour changes could deliver, and at what investment cost. Intensive social interaction (*FD* scenario) leads to 1.4 and 2 times more saved CO_2 emissions in Overijssel and Navarre compared to the *Baseline*. As expected, information policy along with social interactions (*ID* scenario) amplify the impact 1.1 and 1.2 times more on top of the *FD* scenario in Overijssel and Navarre respectively. We observe a non-linear pattern in total investments (Euro per households) under behavioural scenarios over time. When information policy (*ID* scenario) is activated, Dutch households invest 17% more compared to the *FD* scenario in 2020 and this then drops in 2050 (20% less than the *FD* scenario). Spanish household investments in the *ID* scenario increases up to 33% in 2030 and then drops by 5% compared to the *FD* scenario. These nonlinearities emerge from households' preferred actions (I1-3) unequally distributed over time and space (Table 5.1). The three investment actions incur different costs: while investments in energy efficient appliances (I3) is the most popular one (59% in NL and 69% in ES), they form the smallest share of investments in the overall actions in euro. These results are a pure effect of individual changes driven by behavioural factors: we do not include any price-based scenarios (subsidies for green or taxes on grey energy) or changes in technological costs in this article. The last row of Table 1 illustrates the diffusion of Euro investment per actions in two provinces over time.

***Table 5.1** Saved CO_2 and investments of households in two provinces (Overijssel and Navarre) under three behavioural scenarios over time. Source: BENCH-v.3 ABM*

	Scen.	Prov.	2020	2030	2050
Saved CO_2 emission, tons per household	**Baseline**	Overijssel	0.06	0.50	1.09
		Navarre	0.01	0.23	0.78
	FD	Overijssel	0.06	0.71	1.53
		Navarre	0.01	0.47	1.59
	ID	Overijssel	0.06	0.75	1.93
		Navarre	0.09	0.85	1.75
Total investments, in 2016 Euro per household	**FD**	Overijssel	234	2,908	6,858
		Navarre	55	2,198	8,020
	ID	Overijssel	274	2,578	5,430
		Navarre	124	2,931	7,585

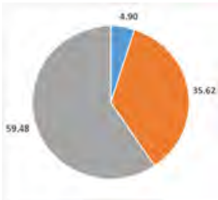
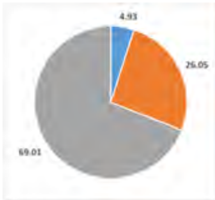
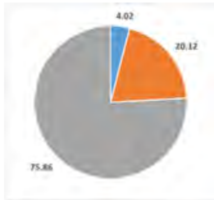
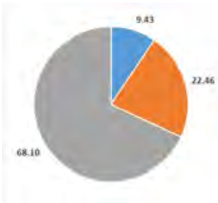
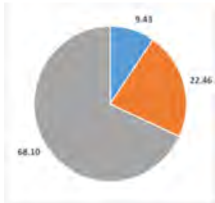
The share of preferred actions, in percentage	Overijssel	I1:4.9% I2: 35.7% I3: 59.4%	I1:4.9% I2: 26.1% I3: 69%	I1:4.0% I2: 20.1% I3: 75.9%
	Navarre	I1:10% I2: 35.2% I3: 54.9%	I1:12.1% I2: 26.7% I3: 61.3%	I1:9.4% I2: 22.5% I3: 68.1%
Total numbe r of actions	Overijssel	443	2,839	6,875
	Navarre	69	1,239	3,690
Investments in 2016 Euro per action, % of total invested money in two provinces I1-Navarre I1-Oveijssel I2-Navarre I2-Overijssel I3-Navarre I3-Overijssel				

5.3.2. Scaling-up behavioural scenarios to national and EU levels (Step 2)

After analysing the dynamics in households' behavioural changes in two provinces over time, we switch to understanding how they change over space. Using population projection scenarios for the EU28, we assess how many households in each age-education group tend to pursue one of the investment actions (Table 5.2). Since behavioural patterns in the survey vary considerably across these sociodemographic groups, scaling up of the provincial patterns from ABM to the entire country changes the patterns in actions. The share of preferred actions in two countries changes over time (Table 5.2). A majority of households – 75.9% and 68.1% – in Spain and the Netherlands intend to invest in energy-efficient appliances (I3) by 2050. The second-best investment action in both cases is to install PVs (I2= 20.1% and 22.5% in 2050). Investments in insulation (I1) is the least popular action (4.1% and 9.4% in NL and ES correspondingly) and it stays stable over time (2020-2050). However, I1 and I2 are expensive investments compared to I3 and consume larger shares of Euro investment (82% in 2050).

Figure 5.6 shows percentage changes in the residential electricity consumption as a result of scaling up the output of the empirical ABM with the population change scenario. Electricity consumption resulting from individual behavioural changes decreases between 56.2-69.5% and 13.8-63.8% by 2050 in the Netherlands and Spain correspondingly. Importantly, there is significant spatial heterogeneity in how behavioural changes diffuse and what regions emerge as laggers or pioneers in bottom-up investments in energy-efficiency. If behavioural patterns elicited through our survey hold in the next few decades, it could be expected that the Limburg, Drenthe, and Zeeland provinces in the Netherlands and the Castile-Leon and Asturias regions in Spain will be pioneers compared to others in respective countries.

***Table 5.2**: Share of actions in two countries over time. Source: scaled-up BENCH-v.3 results.*

		2020	2030	2050
The share of preferred actions, in percentage Insulation Installing PVs Energy-efficient appliances	NL			
	ES			
Total number of actions	NL	3,291	22,026	50,322
	ES	1,546	29,894	123,545

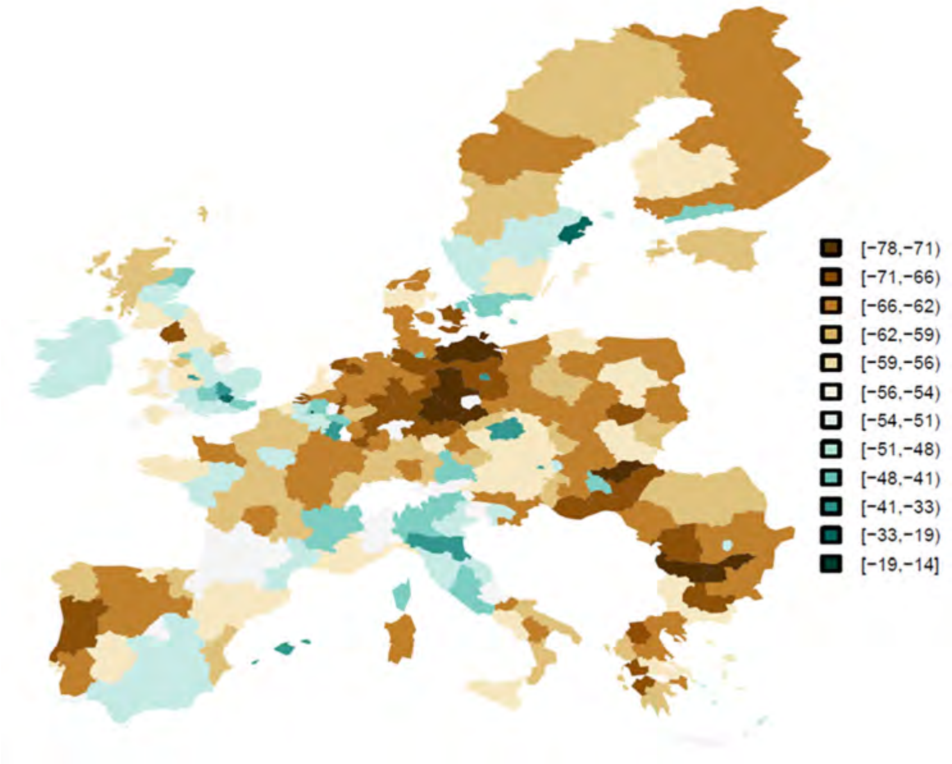


***Figure 5.6**: Percentage change in electricity consumption in 2050 from the base 2015, calculated as a result of scaling up the outcomes of ABM model with population changes in "Fast dynamics" scenario. Source: scaled-up BENCH-v.3 results.*

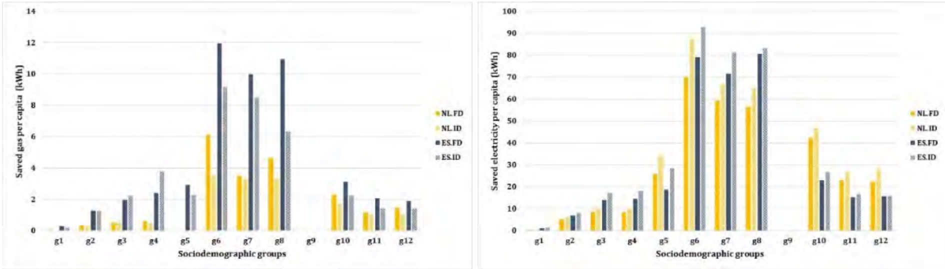
5.3.3. From regional to national and EU28 economy (Step 3)

Scaled–up outputs of the ABM are used as input to the simulation setup of the spatial CGE model. Namely, information from *BENCH-v.3* on the decrease in households' use of electricity and gas is used in order to exogenously modify the minimum subsistence level of households' consumption of the respective services in EU-EMS (see Appendix B on the description of households' demand modelling for more information). A reduction in the consumption of gas and electricity by households results in a higher budget share that becomes available for other types of consumption.

Improvements in energy efficiency may either trigger an increase in energy use (“rebound effect”) or lead to its reduction, causing a shift in households’ spending from energy to other consumption goods. Depending on households’ consumption patterns, such shifts in consumption might result in higher values of GDP over time.

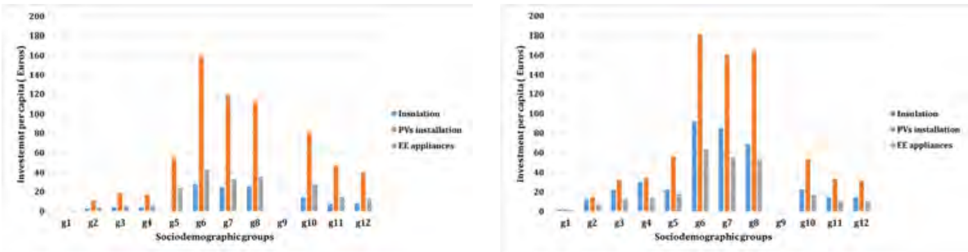
Figures 5.7 and 5.8 illustrate ABM behavioural patterns scaled up through the CGE model for the two countries under different behavioural scenarios. Our analysis demonstrates that households with higher education levels are more likely to change their behaviour compared to low educated people. In both countries, households in the middle education level (ISCED 3 and 4; see Appendix table 5.A.2) are pioneers in saving gas and electricity in 2050, followed by households with high education levels (ISCED 5, 6, and 7; see Appendix table 5.A.2). Importantly, among these higher educated households, younger members (20-40) are more active. In particular, the Dutch youth saves up to 17% and 74% more electricity and gas compared to 40+ households under the *FD* scenario.

Among the pioneers (g6-8, i.e. middle educated and 20+ age; see Appendix table 5.A.2), Spanish households save 1.9-2.8 and 1.0-1.4 times more gas and electricity compared to Dutch households depending on groups and behavioural scenarios. Intensive social dynamics (*FD* scenario) has a stronger impact on saving gas, while the informative *ID* scenario activates more households in saving electricity.



(a) gas (b) electricity

***Figure 5.7**: Saved energy per capita (electricity and gas) as a result of households energy investments among 12 sociodemographic groups under behavioural scenarios (FD,ID) in two countries. Source: EU-EMS and BENCH-v.3*



(a) the Netherlands (b) Spain

***Figure 5.8**: Diffusion of households investments per capita and per action (insulation, PVs installation, energy-efficient appliances) among 12 sociodemographic groups under the informative dynamics scenario in two province. Source: EU-EMS and BENCH-v.3*

As expected, PVs get more of a share of the investments in both countries (Figure 5.8). Households in groups 6-8 invest 110-160 and 160-180 Euros per capita on PVs in Netherlands and Spain respectively, while insulation in Spain (82 Euros per capita) and EE appliances in Netherlands (37 Euros per capita) are second in household investments.

The EU-EMS model operates at the level of NUTS2 regions of the EU28, and hence enables the calculation of the regional impacts of various behavioural scenarios on GDP. Figures 5.9 illustrates the difference in regional GDP levels in 2050 between the *Baseline* and *FD* scenarios. Most of the EU28 regions benefit from the behavioural changes, which leads to a decrease in energy consumption, with a few regions affected negatively. The level of overall GDP impacts depends on the size of the region in terms of population and its share of highly-educated youth. Regions with a larger population as well as the regions with a higher share of highly-educated people benefit more from the behavioural changes since they save more electricity and gas.

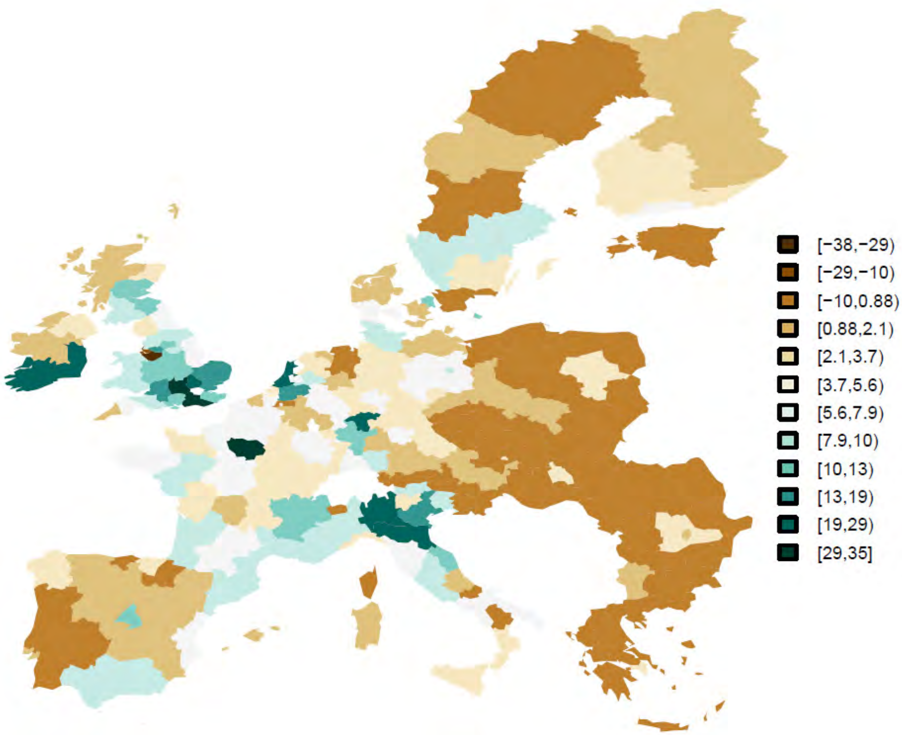


***Figure 5.9**: Deviation in the levels of regional GDP under "Fast dynamics" scenario compared to Baseline in 2050 as an aggregated effect of households' behavioural changes, in millions Euros. Source: EU-EMS and BENCH-v.3*

As Figure 5.10 illustrates, there is a strong positive correlation between the *Baseline* GDP per capita (which is also positively correlated with the share of highly educated persons) and the benefits in terms of additional economic growth per capita from the modelled behavioural changes. This means that rich and economically well-developed regions receive higher benefits from promoting behavioural changes in the long-run compared to the lagging regions.

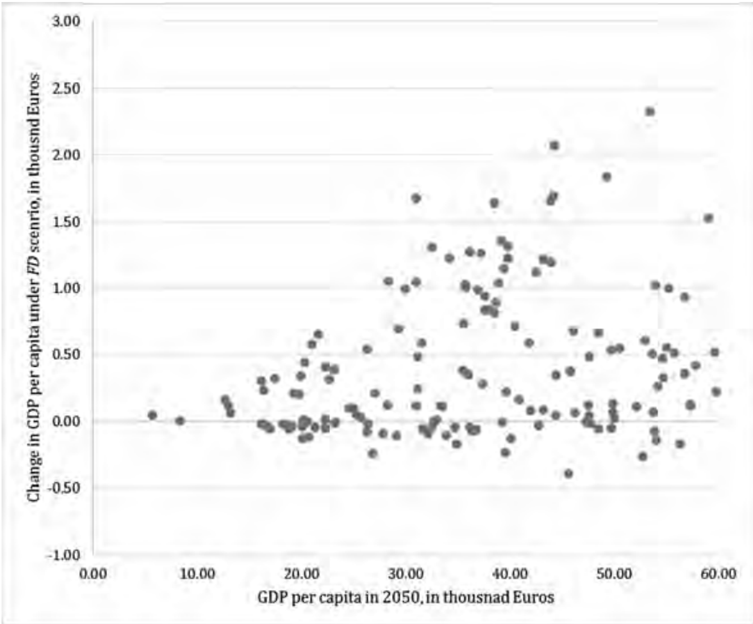


***Figure 5.10**: Correlation between changes in GDP per capital under "Fast dynamics" scenario and the level of regional GDP per capita under "Baseline" scenario in 1000 Euros per individual in 2050. Source: EU-EMS and BENCH-v.3*

This phenomena raises the question of whether the distribution of economic benefits skewed towards rich and well-developed regions increases the overall interregional inequality in Europe. Economists often measure regional disparities using Theil's T inequality index (Eq. 4), the absolute value of which indicates the distance from equality. To understand how behavioural changes under our scenarios impact EU28 regional disparities, we calculate this index for the period 2015-2050 (Figure 5.11).

$$Theil\_T = \frac{\theta_i}{\sum_i \theta_i} \sum_{i=1}^{N} \log\left(\frac{\gamma_i}{\mu}\right) \tag{4}$$

Where θ_o is the GDP of each NUTS2 region, γ_i is the GDP per capita in each region as a measure of regional income, and μ is the average GDP per capita across the EU28 NUTS2 regions.

The dynamics of Theil's T inequality index demonstrate that the inequality between regions decreases in the period of large investments in energy savings (2025-2035) and then starts to increase again over time, indicating the non-linear nature of the process. However, the regional inequality in 2050 does not reach the level of 2015, indicating the positive overall impact of behavioural changes on equality. Despite this, changes in inequality due to the implementation of behavioural scenarios remain modest.

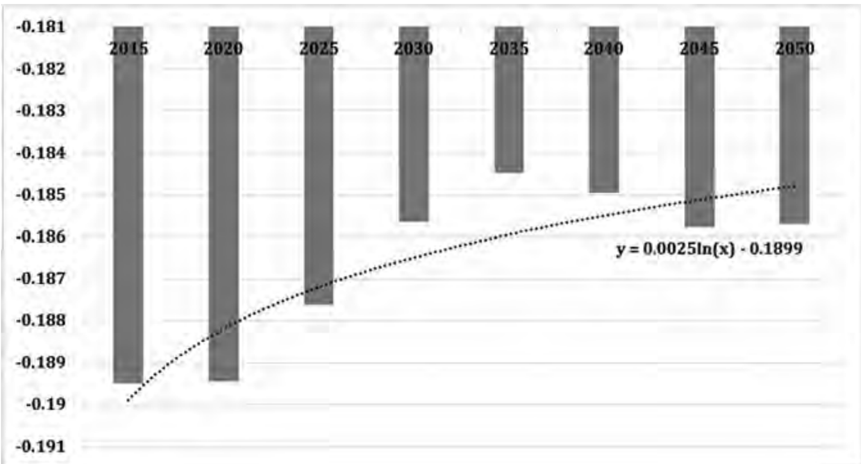


***Figure 5.11**: Dynamics of the Theil-T income inequality index over time under "Fast dynamics". Source: EU-EMS and BENCH-v.3.*

5.4. Discussions and Conclusions

The potential of individual behavioural changes in reducing carbon emissions attracts considerable attention as one of the climate change mitigation strategies (Creutzig et al., 2016; IPCC, 2014a; Niamir et al., 2018b). Comprehensive empirical CGEs, which support quantitative climate change mitigation policy assessments, are strong in tracing cross-sectoral impacts, feedback in the economy as a whole and in linking to readily-available datasets. However, their econometrically-estimated equations reflect past behaviour, making it difficult to integrate behavioural changes (Babatunde et al., 2017; Farmer and Foley, 2009). Moreover, while empirical evidence suggests that individual decision-making deviates from a rational and perfectly informed optimization process, the latter is the core of CGE models (Farmer et al., 2015; Stern, 2016; Wilkerson-Jerde and Wilensky, 2015). ABMs compliment macroeconomic models by accommodating heterogeneity, adaptive behaviour and interactions, bounded rationality, and imperfect information (Rai and Henry, 2016). While ABMs are strong in aggregating heterogeneous adaptive behaviour, they operate on smaller scales of neighbourhoods, cities and regions, omitting feedback to the rest of the economy and cross-sectoral impacts. Survey data is increasingly used to specify individual behavioural rules, yet this behavioural data is not always compatible with the data used in macro models. Linking ABMs and CGE models could ameliorate their weaknesses, if the two types of models are coherently aligned conceptually and data-wise to benefit from their strengths. Methodologically, this article contributes to the ongoing debate (Krook-Riekkola et al., 2017; Parris, 2005; Safarzyńska et al., 2013; Smajgl et al., 2009) on linking these two alien approaches by presenting a method of systematic upscaling of individual heterogeneity and social dynamics to combine ABM and CGE models. The three-step upscaling approach creates a soft-link between ABM and CGE models that permits tracing the macroeconomic and cross-sectoral impacts and indirect effects of individual energy behavioural changes:

1. From behavioural patterns in survey data to cumulative impacts in two provinces

Using our survey data, we specify behavioral rules in the ABM, developed to study shifts in provincial residential energy use and corresponding emissions driven by behavioural changes among heterogeneous individuals. The *BENCH.v3* ABM tracks individual and cumulative impacts of three energy behavioural changes: significant investments in house insulation (I1) or solar panels (I2), and more modest investments in energy-efficient appliances (I3), in the Overijssel and Navarre provinces over 34 years (2016-2050). We introduce three behavioural scenarios (*Baseline*, *FD* and *ID*) differentiated by the intensity of social interactions and the speed of learning among households. Our analysis confirms that faster learning boosted by an information campaign (*FD* vs *Baseline* scenarios) leads to more investments (I2, I3), and consequently to higher electricity savings (40%-100%) in both provinces. In addition, electricity savings increase by 14%-22% in two provinces if pro-environmental awareness is raised through an information policy (*ID* vs *FD* scenarios). However, *ID* has a mixed impact on insulation investments (I1) and gas consumption in Navarre and the opposite effect in Overijssel (*ID* delivers 26% lower gas savings compared to *FD*).

2. Scaling-up behavioural scenarios to the national and EU levels

Using the population projection scenarios for the EU28, we scale the dynamics in household energy behavioural changes in two provinces over time up to national and EU levels. Namely, we define behavioural patterns for a heterogeneous group of households in the Dutch and Spanish regional ABMs. For each of the 12 age-education groups, a number of households perusing an action (I1-3) is estimated together with the average investments, and gas and electricity savings. The analysis reveals that in the Netherlands and Spain that the majority of households – 75.9% and 68.1% – intend to invest in energy-efficient appliances (I3) by 2050. The minority – 4.9% and

9.4% – want to invest in insulation (I1); this trend is stable over time (2020-2050). Electricity consumption resulting from individual behavioural changes decreases between 51-71% (the Netherlands) and 51-66% (Spain) by 2050. In addition, if behavioural patterns and triggers for change elicited through our survey hold in the next decades, it can be expected that the Limburg, Drenthe and Zeeland provinces in the Netherlands and the Castile-Leon and Asturias regions in Spain will become pioneers compared to others in respective countries.

3. From regional to the national and EU28 economy

To estimate the macroeconomic and cross-sectoral impacts of individual energy behavioural changes, we link the up-scaled ABM output to the CGE *EU-EMS* model. The *BENCH-v.3* behavioural patterns in each of the 12 age-education groups – changes in heterogeneous households' electricity and gas consumption – exogenously modify the minimum subsistence level of households' consumption of the respective services in *EU-EMS*. The ABM-CGE results indicate that households with higher education levels are more likely to change their behaviour compared to less educated people. Importantly, among these higher educated households, younger people (20-40) are more active. In particular, Dutch youth saves up to 17% and 74% more electricity and gas compared to 40+ households under the *FD* scenario. In the ABM-CGE model, the reduction in households' energy consumption due to their behavioral changes makes a higher budget share available for other types of consumption. Meanwhile, improvements in energy efficiency may either trigger an increase in energy use ("rebound effect") or lead to its reduction, causing a shift in households' spending from energy to other consumption goods. Therefore, such shifts in behavioral consumption patterns result in higher values of regional GDP over time. The analysis of EU-EMS results indicates that most of the EU28 regions benefit from the behavioural changes and lead to the decrease in energy consumption, with a small number of regions being affected negatively. Importantly, regions with larger population as well as the regions with higher share of highly-educated people benefit more from the behavioural changes since they save more electricity and gas.

The insights of this modeling exercise offer two conclusions. Firstly, we demonstrate the feasibility and importance of introducing heterogeneity and behavioural-rich dynamics in assessing climate change mitigation polices. We develop a transparent soft-linkage step-wise process to integrate an empirical behaviourally-rich ABM and a spatial CGE model. To the best of our knowledge, this is the first attempt to link empirical ABM and CGE to estimate the macroeconomic impacts of individual energy behavioural changes.

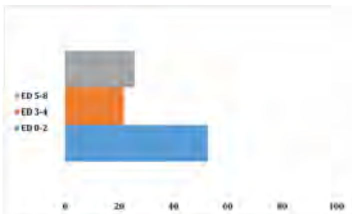
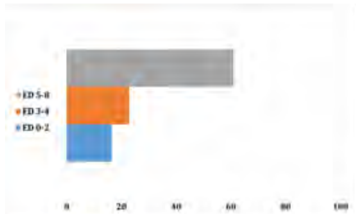
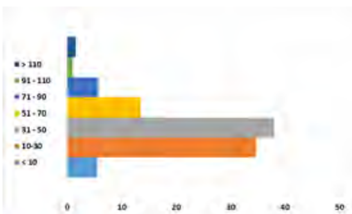
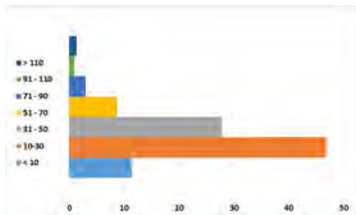
Secondly, this research demonstrates that the regional dimension is important for a low-carbon economy transition. Some regions lag behind while others are pioneers, due to the heterogeneity in individuals' sociodemographics (e.g. education and age), structural characteristics (e.g. type and size of dwellings), behavioural and social traits, and spatial characteristics (e.g. urban vs. rural). In addition, the inequality between regions decreases in the period of large investments (2015-2035) and starts to increase over time following it. However, the regional inequality in 2050 does not reach the level of 2015. Hence, the soft-link integrated ABM-CGE model elicits dynamic effects of climate change mitigation behavioural solutions and traces how regional demographics may amplify economy-wide impacts of individual energy use practices.

Future work could focus on a two way dynamic integration – hard-link – whereby two empirical models could be linked using software wrappers or modern web-interfaces for models' integration (Belete et al., 2018). In addition, the ABM could benefit from integrating this behaviourally rich demand side modelling with dynamics of dwelling stock. The static and aging housing should be replaced by scenarios of its structural development and technological progress in new urban developments (e.g. zero-carbon footprint buildings) and refurbishing old housing stock in cities.

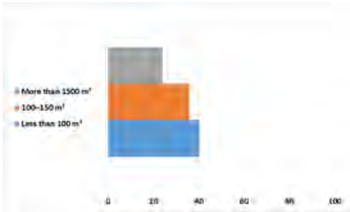
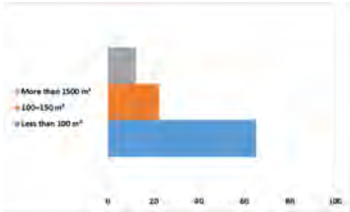
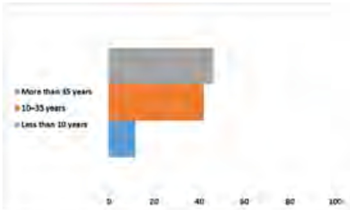
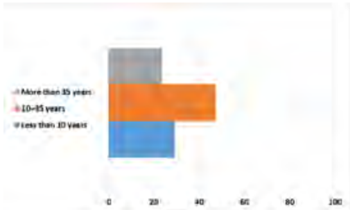
Appendix A

The agent-based *BENCH v.3* model is parameterized using the survey data on socio-demographic, economic, structural and behavioural attributes of households and their dwelling characteristic (Table 5.A.1).

Table 5.A.1*: Survey data on households' characteristics and behavioural intentions. The data is used to parameterize households' behaviour in the BENCH.v3 ABM. Source: Niamir et al. (2018d)*

Factors	**Overijssel**	**Navarre**
Socio-demographic characteristics		
Gender	Female: 46.4% Male: 53.6%	Female: 57.1% Male: 42.9%
Age, years	53	41
Education, ISCED*		
Annual income, in thousand Euros per year		
Dwelling characteristics		

* https://ec.europa.eu/eurostat/statistics-explained/index.php/International_Standard_Classification_of_Education_%28ISCED%29#Implementation_of_ISCED_2011_.28levels_of_education.29

Type of residence	Apartment : 14.9% House: 85.1%	Apartment : 77.8% House: 22.2%
Tenure status	Owner: 71% Renter: 29%	Owner: 80.3% Renter: 19.7%
Size of residence		
Age of residence		
Behavioural characteristics, value on the 1-7 scale		
CEE Knowledge	4.2 (0.7)	5.0 (0.8)
CEE Awareness	4.9 (0.8)	5.4 (0.8)
ED Awareness	4.5 (1.0)	5.3 (1.1)
Personal Norms	4.6 (0.9)	5.4 (1.0)
Social Norms	3.3 (1.1)	4.5 (1.2)
Perceived Behaviour Control	4.4 (1.1)	5.0 (1.3)

The actions and patterns of behavioural processes of heterogeneous households in *BENCH-v.3* are further aggregated per socio-demographic group (Table 5.A.2). Education level and age appear to be the main determinants of households' energy-efficiency investments according to the survey results (Niamir et al., 2018d).

***Table 5.A.2**: Socio-demographic groups, based on the Eurostat classification*

Group number	Education level (1-3)	Age group (1-4)
G1	Low (ISCED 0-2)	1 (younger than 20)
G2	Low (ISCED 0-2)	2 (20-40 years old)
G3	Low (ISCED 0-2)	3 (40-60 years old)
G4	Low (ISCED 0-2)	4 (older than 60)
G5	Middle (ISCED 3-4)	1 (younger than 20)
G6	Middle (ISCED 3-4)	2 (20-40 years old)
G7	Middle (ISCED 3-4)	3 (40-60 years old)
G8	Middle (ISCED 3-4)	4 (older than 60)
G9	High (ISCED 5-8)	1 (younger than 20)
G10	High (ISCED 5-8)	2 (20-40 years old)
G11	High (ISCED 5-8)	3 (40-60 years old)
G12	High (ISCED 5-8)	4 (older than 60)

We estimate the annual change in the population in all EU28 NUTS2 regions using the projections from EUROPOP2008 Eurostat (Fig. 5.A.1).

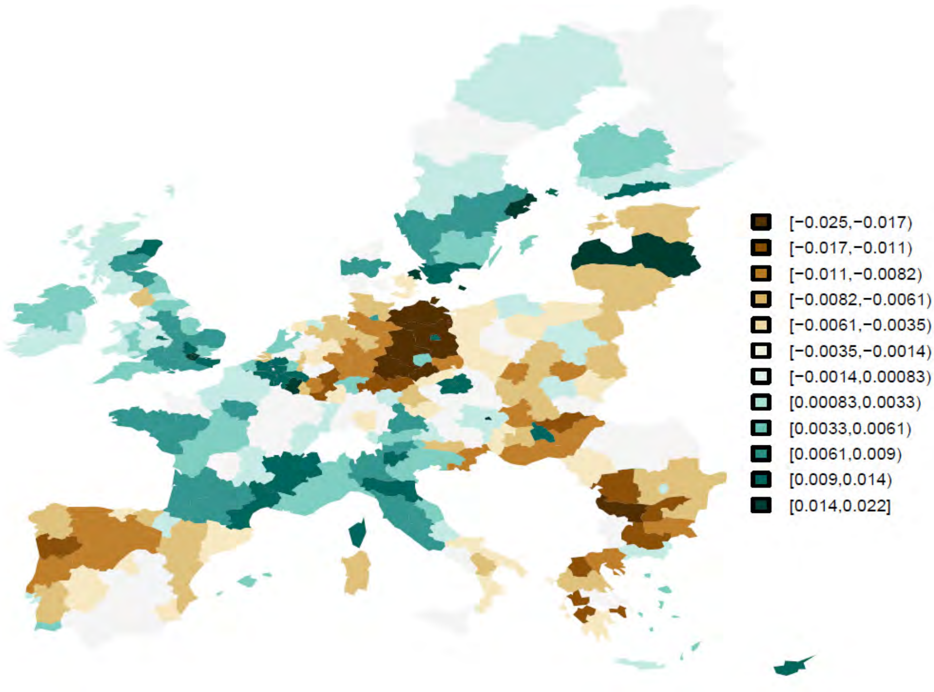


Figure 5.A.1*: Average annual percentage change in the population of EU28 NUTS2 regions in the period 2015-2050*

Appendix B

This section provides the technical details of the EU-EMS CGE model.

Regional structure of the model

Regions differ by the type of production sectors which dominate overall production activities in the region. Some specialize in traditional sectors like agriculture, whereas others specialize in modern sectors such as finance and industry. Those sectors are characterized by different level of agglomeration and its importance. Traditional sectors do not experience any agglomeration effects whereas modern sectors do and that allows some sectors to grow faster than the other ones. The prototype model will incorporate the regional difference in sectoral specialization and hence the difference of agglomeration economies between the regions.

AUS	Australia	ARG	Argentina
AUT	Austria	BGR	Bulgaria
BEL	Belgium	BRA	Brazil
CAN	Canada	BRN	Brunei Darussalam
CHL	Chile	CHN	China
CZE	Czech Republic	CHN.DOM	China Domestic sales only
DNK	Denmark	CHN.PRO	China Processing
EST	Estonia	CHN.NPR	China Non processing goods exporters
FIN	Finland	COL	Colombia
FRA	France	CRI	Costa Rica
DEU	Germany	CYP	Cyprus
GRC	Greece	HKG	Hong Kong SAR
HUN	Hungary	HRV	Croatia
ISL	Iceland	IDN	Indonesia
IRL	Ireland	IND	India
ISR	Israel	KHM	Cambodia
ITA	Italy	LTU	Lithuania
JPN	Japan	LVA	Latvia
KOR	Korea	MLT	Malta
LUX	Luxembourg	MYS	Malaysia
MEX	Mexico	PHL	Philippines
MEX.GMF	Mexico Global Manufacturing	ROU	Romania
MEX.NGM	Mexico Non-Global Manufacturing	RUS	Russian Federation
NLD	Netherlands	SAU	Saudi Arabia
NZL	New Zealand	SGP	Singapore
NOR	Norway	THA	Thailand
POL	Poland	TUN	Tunisia
PRT	Portugal	TWN	Chinese Taipei
SVK	Slovak Republic	VNM	Viet Nam
SVN	Slovenia	ZAF	South Africa
ESP	Spain	RoW	Rest of the world
SWE	Sweden		
CHE	Switzerland		
TUR	Turkey		
GBR	United Kingdom		
USA	United States		

Household preferences and governmental sector

The households' and governmental demand for goods and services is represented by the Linear Expenditure System (LES) that is derived as a solution to the Stone-Geary utility maximisation problem:

(5)

$$U_r = \prod_i \left(C_{ri} - \mu_{ri}\right)^{\gamma_{ri}}$$

The resulting demand system where I_r denotes households' disposable income and P_{ri} are consumer prices of goods and services that include taxes, subsidies, transport and trade margins can be written as follows

(6)

$$C_{ri} = \mu_{ri} + \gamma_{ri} \cdot \frac{1}{P_{ri}} \cdot \left(I_r - \sum_j \mu_{rj} \cdot P_{rj} \right)$$

Households always consume a certain minimum level of each good and services where this level reflects the necessity (or price elasticity) of the good or service. Necessities such as food have low price elasticity and hence higher minimum level of consumption. The disposable income of the households consist of wages, return to capital, social transfers from the government minus the income taxes and households' savings.

The government collects production, consumptions and income taxes. The tax revenue is further used to pay social transfers and buy goods and services for public consumption. The governmental savings can be either endogenous or exogenous in the model depending on the type of simulation and the type of chosen macro-economic closure.

Firms production

Domestic production X_{ri}^{D} is obtained using the nested-CES production technology of Capital-Labour-Energy-Materials (KLEM) type, where K is the capital, L is the labour, E is the energy and M is the materials. Figure II.2 represents the nests in the KLEM production function used in the model with services between used according to the fixed Leontief input coefficients in the production process. The energy in the model is differentiated between electricity and other types of energy with some substitution possibilities between them. The labour is differentiated according to three education levels according to International Labour Organisation (ILO) classification [ref].

The domestic production is generated according to nested production CES function that is described by the following set of composite CES functions that follow the production structure from top to the bottom nest

(7)

$$X_{ri}^{D} = \left[\left(a_{ri} \cdot M_{ri} \right)^{\rho_{M,KLE}} + \left((1-a_{ri}) \cdot KLE_{ri} \right)^{\rho_{M,KLE}} \right]^{1/\rho_{M,KLE}}$$

(8)

$$KLE_{ri} = \left[\left(b_{ri} \cdot E_{ri} \right)^{\rho_{E,KL}} + \left((1-b_{ri}) \cdot KL_{ri} \right)^{\rho_{E,KL}} \right]^{1/\rho_{M,KLE}}$$

(9)

$$KL_{ri} = \left[\left(c_{ri} \cdot K_{ri} \right)^{\rho_{K,L}} + \left((1-c_{ri}) \cdot L_{ri} \right)^{\rho_{K,L}} \right]^{1/\rho_{K,L}}$$

(10)

$$E_{ri} = \left[\left(d_{ri} \cdot E_{ri}^{NELEC} \right)^{\rho_{E}} + \left((1-d_{ri}) \cdot E_{ri}^{ELEC} \right)^{\rho_{E}} \right]^{1/\rho_{E}}$$

(11)

$$L_{ri} = \left[\sum_{e} \left(f_{rie} L_{rie}^{ED} \right)^{\rho_L} \right]^{1/\rho_L}$$

Where a_{ri} , b_{ri}, c_{ri} , d_{ri} and f_{rie} are the share parameters of the corresponding production function nests and $\rho_{M,KLE}$, $\rho_{E,KL}$, $\rho_{K,L}$, ρ_E and ρ_L represent the substitution possibilities for each of the production function nests. The inputs into the production are denoted as M_{ri} input of materials, KLE_{ri} composite capital-labor-energy nest, E_{ri} energy inputs, KL_{ri} composite capital-labor nest, K_{ri} capital input, L_{ri} labor input, E_{ri}^{NELEC} input of non-electric energy, E_{ri}^{ELEC} input of electric energy and L_{rie}^{ED} inputs of labor by type of education e.

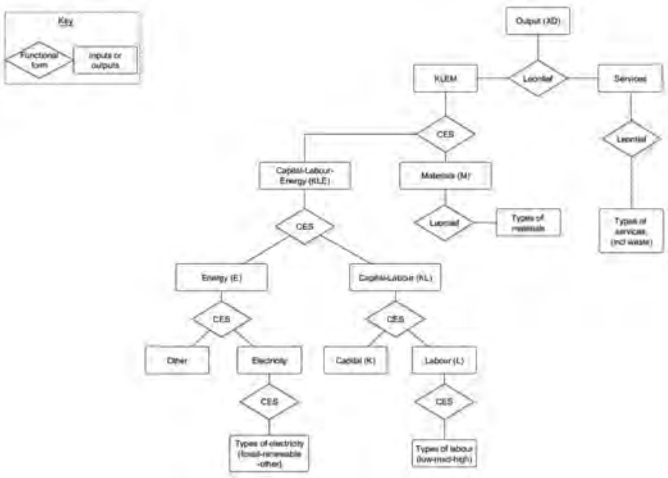


***Figure B-1**: Structure of KLEM production functions in the model*

International and inter-regional trade

The total sales X_{ri} of tradable goods and services i in region r in the model is an Armington Constant Elasticity of Substitution (CES) [ref] composite between domestic output X_{ri}^{D} and imports X_{ri}^{M} such that

(12)

$$X_{ri} = \left[\left(\alpha_{ri}^{D} \cdot X_{ri}^{D} \right)^{\rho_i} + \left(\alpha_{ri}^{M} \cdot X_{ri}^{M} \right)^{\rho_i} \right]^{1/\rho_i}$$

Where α_{ri}^{D} and α_{ri}^{M} are the calibrated share parameters of the CES function and $\rho_i = \frac{\sigma_i - 1}{\sigma_i}$ with σ_i being the Armington elasticity of substitution between domestic and imported tradable goods and services. The elasticity of substitution varies between different types of goods and services depending on the available empirical estimates. In case of non-tradable the composite is equal to the domestically produced product.

Imported goods can come from various regions and countries represented in the model and the composite imported goods and services are represented by CES composite that uses a higher Armington elasticity of substitution as compared to the upper Armington nest. We assume as in the GTAP model that the elasticity of substitution between the same type of goods and services coming from different countries is twice as large as the elasticity of substitution between domestic and aggregate imported goods and services. The aggregate imported good is calculated according to the following CES composite function

(13)

$$X_{ri}^{M} = \left[\sum_{s} \left(\alpha_{sri}^{T} X_{sri}^{T} \right)^{\rho_i^T} \right]^{1/\rho_i^T}$$

Where α^{T}_{sri} is the calibrated share coefficient of the CES production function, X^{T}_{sri} is the flow of trade in commodity i from country s to country r. The coefficient $\rho^{T}_{i} = \frac{\sigma^{T}_{i} - 1}{\sigma^{T}_{i}}$ where σ^{T}_{i} is the elasticity of substitution between commodities produced in different countries.

Labour, capital and goods markets

Market equilibrium in the economy results in equalization of both monetary values and quantities of supply and demand. Market equilibrium results in equilibrium prices that represent in case of CGE models the solution to the system of nonlinear equations that include both intermediate and final demand equations as well as accounting constraints that calculate households' and government incomes, savings and investments as well as trade balance. EU-EMS model represent a closed economic system meaning that nothing appears from nowhere or disappears into nowhere in it. This feature of the CGE model constitutes the core of the Walrasian equilibrium and ensures that even if one excludes any single equation of the model it will still hold. This is the property of CGE models called Walras law that tells us that in the closed economic system if n-1 markets are in equilibrium the last n^{th} market will also be in equilibrium.

In our EU-EMS model the static equilibrium is described by the set of commodity and factor prices, total outputs, final demands of households and government, investments, savings and net transfers from abroad such that (1) markets for goods and services clear, (2) total investments are equal to total savings, (3) total households consumption is equal to their disposable income minus savings, (4) total governmental consumption is equal to its net tax revenues minus transfers to households minus savings, (5) total revenue of each economic sector is equal to its total production costs and (6) difference between imports and exports is equal to the net transfers from abroad.

Recursive dynamics

EU-EMS is a dynamic model and allows for the analysis of each period of the simulation time horizon. This horizon is currently set at 2050 but it can be extended to longer time periods. For each year of the time horizon, EU-EMS calculates a set of various economic, social and environmental indicators. The economic growth rate in EU-EMS depends positively on investments in R&D and education. By investing in R&D and education each region is able to catch up faster with the technological leader region and better adopt its technologies.

Time periods in EU-EMS are linked by savings and investments. By the end of each time period, households, firms and government in the model save a certain amount of money. This money goes to the investment bank, distributing it as investments between the production sectors of the various regions. The allocation decisions of the investment bank sectors depend on the sector's financial profitability. The model runs in time steps of five years for the period 2015-2050.

The capital stocks evolve according to the dynamic rule presented below, where the capital stock in period t is equal to the capital stock in period t-1 minus the depreciation plus the new investments into the capital stock

$$K_{tri} = K_{t-1ri}(1-\delta_i) + I_{tri} \tag{14}$$

At the end of each period there is a pool of savings S_r available for investments into additional capital stocks of the sectors. This pool of savings comes from households, firms and foreign investors. The sector investments

I_{tri} are derives as a share of the total savings in the economy according to the discrete choice formula

(15)

$$I_{tri} = \frac{ST_{t-1r} B_{ri} K_{t-1ri} e^{\vartheta \cdot WKR_{t-1ri}}}{\sum_j B_{rj} K_{t-1rj} e^{\vartheta \cdot WKR_{t-1rj}}}$$

(16)

$$WKR_{t-1ri} = \frac{r_{t-1ri}}{PI_{t-1r}} \cdot (g_r + \delta_{ri})$$

Where WKR_{t-1ri} denotes the capital remuneration rate, g_r the steady-state growth rate, B_{ri} the calibrated gravity attraction parameter and ϑ the speed of investment adjustments.

Chapter 6:

SYNTHESIS AND OUTLOOK

6.1. Introduction

It has been proven that human activities and the associated increasing emissions of greenhouse gases (GHGs) are the main reasons for global warming (Hertwich and Peters, 2009; IPCC, 2014b; Oreskes, 2004). On a global scale, households influence, directly and indirectly, 72% of GHG emissions (Hertwich and Peters, 2009), and Baiocchi et al. (2010) report that 74% of total consumer emissions of CO_2 are influenced by households (directly and indirectly) in the UK. Among this 74%, 12.6% comes from direct household domestic energy consumption. Based on Eurostat, household energy consumption is the main cause of the observed GHG emissions. European households are responsible for almost one-quarter of total energy consumption in Europe.[*] CO_2 is one of the gases that contribute to the greenhouse effect and is the most important long-lived gas that "forces" climate change.[†] Decarbonization of the economy requires massive worldwide efforts and a strong involvement of regions, cities, businesses, and individuals in addition to commitments at national levels (Creutzig et al., 2018a; Grubler et al., 2018).

Mitigating anthropogenic climate change requires urgent understanding of which human activities are more culpable, what causes them, and how we can effectively change them. However, explaining and affecting human behaviour is a difficult task since human nature is complex and heterogeneous. Quantitative tools to assess cumulative household emissions, given the diversity of behaviour and a variety of psychological and social factors influencing it beyond purely economic considerations, are scarce.

[*] Total energy arriving at and consumed by end users, such as households, industry, agriculture, and so forth. https://climatepolicyinfohub.eu/household-contribution-buildings-carbon-footprint

[†] https://climate.nasa.gov/causes/

Current economic energy models (usually based on equilibrium and optimization assumptions) provide very limited representations of household heterogeneity and treat households as purely rational decision-making units.

This Ph.D. research aims to assess the contribution of individual behaviour changes to climate change mitigation at different scales. To address this scientific challenge, I have: (a) designed and conducted a comprehensive household survey to explore how individuals choose to change their energy-related behaviour and what factors trigger or inhibit these choices (Chapter 2); (b) designed and developed simulation tools to aggregate these insights and quantitatively assess regional and national impacts of individual choices (Chapters 3 and 4); and (c) investigated and presented a solution to upscaling individual energy behaviour for climate change mitigation strategies (Chapter 5). This dissertation addresses a number of research questions. The following section offers an overview of findings on each of them one-by-one.

6.2. Overview of findings

Research Question 1: What are the main factors influencing individual energy behavioural changes in the transition to a low-carbon economy?

To address this question, I analysed contributions of households' behavioural, socio-demographic, and structural dwelling characteristics based on the unique data from an extensive survey (N=1,790) from two provinces in EU member states (Niamir et al., 2018d). The goal was to quantify which factors – socioeconomic (e.g., income, age), behavioural (e.g., personal and social norms), and structural (e.g., size and type of house) – trigger or attenuate a transition to a lower-energy footprint at the household level. To address this goal, I examined determinants of three individual energy behaviours: investment, conservation, and switching to "green" providers by employing correlation and probit regression analyses. The innovative contribution of this paper is threefold:

- *Empirical testing of theoretical concepts*: Relying on theories on individual decision making from psychology, this thesis develops a conceptual framework that integrates a variety of behavioural factors potentially relevant for studying energy behaviour changes. The role of various behavioural factors is quantitatively studied using original survey data.
- *Heterogeneity*: Our analysis goes beyond the current empirical literature on individual energy behaviour by focusing on detailed actions within the three main types of household choices: investment, conservation, and switching among providers. Within these three sets, we examine nine different actions and their dependence on both socioeconomic and behavioural characteristics of households as well as on structural dwelling factors. Hence, our quantitative assessment exceeds aggregates, acknowledging the fact that various socioeconomic groups may exhibit different behavioural traits for different actions.
- *Comparative analysis*: The two countries in our sample permit us to compare households' choices and the role of behavioural factors across contexts. On the one hand, it allows testing of whether behavioural factors included in the theoretical framework matter in different cases, strengthening the validity of the proposed theoretical framework. On the other hand, a comparison across countries accounts for institutional, cultural, and climatic factors that do affect households' choices but which are often difficult to capture explicitly.

A survey was designed and conducted in two provinces in Europe that differ in terms of climate, culture, GDP, technology innovation and diffusion processes, renewable energy sources, institutional rules, and policies.

During the summer of 2016, 1,035 households in the Overijssel province, Netherlands (NL), and 755 households in the Navarre province, Spain (ES), completed an online questionnaire. The analysis of this data provides strong evidence of the importance of behavioural factors in making energy-related decisions and in promoting behavioural changes which are essential for a transition to a low-carbon economy in Europe. Several behavioural factors, such as knowledge and awareness, influence personal norms (0.45-0.77 correlation). The higher the level of knowledge and awareness about environmental and climatic issues, the higher the level of personal norms. The impact of the societal, institutional rules – culture, fiscal rules, and regulations – on individuals is inevitable, as confirmed by the significant (99% confidence interval) effect of the country variables (NL vs. ES).

Moreover, households are not making decisions in isolation, as they are prone to being influenced by peers in their social networks. Social norms have an essential role in shaping personal norms. Together, personal and social norms can trigger individuals to make energy-efficient decisions.

Among dwelling characteristics, the type, size, and age of the residence have a strong influence on energy investments and conservation. As expected, people living in a house are more eager to pursue larger investments than people renting an apartment (0.4-0.5, 99% confidence interval). They also have more incentives to save energy by turning down the heater/air conditioner (0.3, 99% confidence interval). Analysis of socio-demographic factors highlights the role of education in household energy-related decisions, particularly in energy investments and in switching to green-energy sources. Educated households are more active in improving their energy efficiency in both case studies (0.05-0.08, 99% confidence interval). A higher level of education enables more insight, knowledge, and awareness of the environment in terms of climate–energy issues, which all, consequently, affect personal norms and lead to a behavioural change.

To conclude, the empirical analysis demonstrates that behavioural factors, next to structural factors and education, play at least as important a role in energy use decisions – investment, conservation, and switching – as monetary factors, such as income.

Research Question 2: To what extent does heterogeneity in households' attributes, social interactions, and learning impact regional energy demand over time?

Survey data provide invaluable information about the behavioural patterns of heterogeneous households, yet the aggregated impacts of these individual decisions are not evident. To quantify the cumulative impacts of household behavioural changes on regional dynamics of saved energy and CO_2 emissions, I designed a computational agent-based model. The *BENCH* model, which is based on the survey data, permits the study of the large-scale, regional effects of individual actions and exploration of how they may change over time. The model explicitly treats behavioural triggers and barriers at the individual agent level, assuming that decision making about energy use is a multi-stage cognitive process. This thesis presents the results of simulations over 14 years (2016–2030), assuming the business-as-usual (SSP2) scenario for the supply side, which provides for the growth of energy production till 2030. By running several simulation experiments, I add complexity gradually to explore the impact of heterogeneity, psychological factors, and learning and social networks on the energy-related behavioural changes of households and the aggregated provincial impacts of these changes. The results indicate that pro-environmental individual energy choices and behavioural changes depend on social interactions and learning at different stages of households' decision making. Cumulatively, these individual choices have significant economic consequences.

The simulation and analysis show that when household economic and housing attributes are heterogeneous, there is a significant increase in the diffusion of energy actions and that this trend is nonlinear. The results illustrate that spreading knowledge and motivation regarding energy-efficient practices via social networks helps to decrease the provincial energy use by 14,751 MWh, while increasing the private economic benefits by up to 46,000 Euro and preventing more than 3,200 t of CO_2 emissions by 2030.

Research Question 3: What are the macroeconomic impacts of individuals' behavioural changes on carbon emissions?

To assess the impact of individual behaviour on carbon emissions, the *BENCH-v.1* agent-based model (Niamir et al., 2018b) is developed further by strengthening the alignment of behavioural and economic factors under different climate policy scenarios. I calibrated the *BENCH-v.2* model using data on households' energy-related choices from the survey described above (Question 1). The *BENCH-v.2* (Niamir et al., 2018e) calculated changes in electricity consumption annually and implied carbon emissions based on the primary source of energy by simulating individuals' behaviour under different end-user behavioural and climate scenarios.

The results indicate that accounting for demand-side heterogeneity provides a better insight into possible transition pathways to a low-carbon economy and climate change mitigation. Namely, the model including household heterogeneity, as represented by socio-demographic, dwelling, and behavioural factors, shows rich dynamics and provides a more realistic image of socioeconomics by simulating the economy through the social interactions of heterogeneous households. I analysed four end-user scenarios, which varied from the baseline scenario through the introduction of agent heterogeneity, the intensity of social interactions among households (slow or fast), and the lack or presence of carbon price (€10, €25, or €50 per ton). By comparing end-user scenarios, the relative impact of bottom-up drivers (social dynamics and learning on the diffusion of information) and top-down market policies (carbon price) on carbon emission reduction are estimated.

The impact of household attribute heterogeneity and social dynamics brings about a 5%-9% CO_2 emission reduction by 2030. Adding carbon price cuts CO_2 emission down to 55% compared to the baseline scenario, which mimics the traditional economic setup of a representative rational, fully-informed household making the optimal decision.

Research Question 4: What is a systematic way of upscaling behavioural aspects of individual decision-making to assess macroeconomic impacts for climate change mitigation over time and space?

ABM and Computable General Equilibrium (CGE) models each have their own assumptions, strengths, and weaknesses. As a typical macroeconomic model, a CGE model has a "top-down" approach, in contrast with behaviourally-rich, "bottom-up," out-of-equilibrium ABM simulations. To trace macro-level effects, CGE models aggregate the preferences of various actors by assuming a representative rational, fully-informed agent capable of making the optimal choice. Behavioural changes, including behavioural climate change mitigation actions, for example, driven by an increased level of knowledge regarding climate change in society and shifts in preferences, are difficult to integrate. To be able to analyse the macroeconomic and sectoral impacts of such behavioural changes, CGE models rely on complimentary micro-modelling tools such as AMBs.

This dissertation presents a novel method for the systematic upscaling of individual heterogeneity and social dynamics by combining the strengths of the ABM and CGE models. The three-step upscaling approach suggested in this thesis creates an integrated ABM-CGE model that permits tracing the macroeconomic and cross-sectoral impacts and indirect effects of individual energy behavioural changes. Chapter 5 of this dissertation presented the soft link of the *BENCH-v.3* ABM and *EM-EMS* CGE models.

Here, the *BENCH* model (Niamir et al., 2018b; Niamir et al., 2018e) has been developed further to investigate the role of individual energy behavioural changes in the transition to a low-carbon economy. Namely, agents' utility functions are modified to align empirically-grounded energy decisions from the households' surveys with macroeconomic dynamics in our data-driven CGE model. In particular, *BENCH-v.3* focuses on energy investments that households may decide to undertake: significant investments in house insulation (I1) or solar panels (I2) and more modest investments in energy-efficient appliances (I3). The *BENCH-v3* model tracks the individual and cumulative impacts of three energy behavioural changes among heterogeneous individuals in the Overijssel and Navarre provinces over 34 years (2016-2050).

EU-EMS is a spatial computable general equilibrium (SCGE) model developed by the PBL Netherlands Environmental Assessment Agency and is used for policy impact assessment. The current version of EU-EMS covers 276 NUTS2 regions of the EU28 member states. Goods and services are consumed by households, government, and firms and are produced in markets that can be perfectly or imperfectly competitive. Spatial interactions between regions are captured through the trade in goods and services, factor mobility, and knowledge spill-overs.

In order to link *BENCH-v.3* and *EM-EMS,* a novel systematic three-step method is presented:

- *From behavioural patterns in survey data to cumulative impacts in two provinces*: The *BENCH-v.3* is presented to study shifts in provincial residential energy use and corresponding emissions driven by behavioural changes among heterogeneous individuals. Particularly, the *BENCH-v.3* model tracks individual and cumulative impacts of three energy behavioural changes – significant investments in house insulation (I1) or solar panels (I2) and more modest investments in energy-efficient appliances (I3) – in the Overijssel and Navarre provinces over 34 years (2016-2050). Here, three behavioural scenarios (*Baseline*, *FD*, and *ID*) are introduced, which are differentiated according to the intensity of social interactions and the speed of learning among households. The analysis shows faster learning boosted by an information campaign, as expected, leads to more investments (I2, I3) and, consequently, to higher electricity savings (40%-100%) in both provinces (*FD* vs *Baseline* scenarios). In addition, electricity savings increase 14%-22% more in two provinces if pro-environmental awareness is raised through an information policy (*ID* vs *FD* scenarios). However, *ID* has a mixed impact on insulation investments (I1) and gas consumption in Navarre and the opposite effect in Overijssel (*ID* delivers 26% lower gas savings compared to *FD*).

- *Scaling-up behavioural scenarios to national and EU levels:* Here, with the help of population projection scenarios for EU28, the dynamics in household energy behavioural changes in two provinces over time are scaled up to national and EU levels. To do this, behavioural patterns for a group of households are defined in the Dutch and Spanish regional ABMs separately. For every 12 education-age household groups, the number of households perusing an action (I1-3) is estimated, and, correspondingly, average gas and electricity savings and investments are calculated. The analysis shows that, in the Netherlands and Spain, the majority of households,75.9% and 68.1%, respectively, intend to invest in energy-efficient appliances (I3) by 2050. Minorities, 4.9% and 9.4%, respectively, are willing to invest in insulation (I1) and these percentages stay stable over time (2020-2050). Electricity consumption resulting from individual behavioural changes decreases between 51-71% and 51-66% by 2050 in the Netherlands and Spain, respectively. Importantly, there is significant spatial heterogeneity in how behavioural changes are diffused and what regions emerge as lagers or pioneers in bottom-up investments in energy-efficiency. If behavioural patterns elicited through the survey hold in the next decades, one could expect that Limburg, Drenthe, and Zeeland provinces in the Netherlands and Castile-Leon and Asturias regions in Spain will pioneer compared to others in respective countries.

- *Behavioural changes and their impacts on regional economies, from regional changes to EU28 GDP impacts*: The *EU-EMS* CGE model is presented to facilitate the tracing of the macroeconomic and cross-sectoral impacts and indirect effects of individual energy behavioural changes. In this step, the scaled-up *BENCH-v.3* information, namely, changes in heterogeneous households' electricity and gas consumption, is used to modify exogenously the minimum subsistence level of households' consumption of the respective services in EU-EMS. The analysis of scaled-up *BENCH-v.3* behavioural patterns through *EU-EMS* shows households with higher education levels are more likely to change their behaviour compared to low-educated people. Importantly, among these higher-educated households, younger members (20-40) are more active. Particularly, Dutch youths save 17%-74% more electricity and gas compared to 40+-age households under the *FD* scenario. The changes (reduction) in households' energy consumption resulting from their behavioural changes make a higher budget share available for other types of consumption. Meanwhile, improvements in energy efficiency may either trigger an increase in energy use ("rebound effect") or lead to its reduction, causing a shift in households' spending from energy to other consumption goods. Therefore, such shifts in behavioural consumption patterns results in higher values of GDP over time. The analysis of the EU-EMS results indicates that most of the EU28 regions benefit from the behavioural changes and lead to the decrease in energy consumption, with a small number of regions being affected negatively. Importantly, regions with a larger population as well as the regions with a higher share of highly-educated people benefit more from the behavioural changes since they save more electricity and gas.

To conclude, Chapter 5 of this dissertation brought attention to the potential of heterogeneous individual energy behavioural changes in terms of the transition to a low-carbon economy at national and EU levels. Moreover, it highlighted that this transition varies from one region to another. Some regions are lagging behind and others are moving ahead due to heterogeneity in individual sociodemographic (e.g., education and age) and structural characteristics (e.g., type and size of dwellings), behavioural and social traits, and spatial characteristics (e.g., urban vs. rural). In addition, the analysis on the inequality index shows the inequality between regions is decreasing in the period of large investments in insulation, PVs, and energy-efficient appliances and starts to increase over time after this period. However, the regional inequality, in 2050, does not reach the level of 2015. This tool is ideal for studying the dynamic effects of climate change mitigation policy measures targeted at changes in individual energy use practices.

6.3. Innovation

This dissertation contributes to the scientific efforts to bridge the gap between a stylized representation of human decision-making in current energy-economy models and the rich evidence on pro-environmental behaviour that social sciences provide. The models, data, and insights delivered by this dissertation make a number of innovative contributions to science:

The unique micro-level dataset on behaviour**:** By designing and conducting a comprehensive survey among households in two European regions, I explored the individual energy consumption practices and behavioural aspects that may influence them. Notably, this dissertation investigated the internal and external drivers that can change the behavior of households and which ones are barriers that can delay the decision process (Chapter 2). The novelty of this work is fourfold:

- *Empirical testing of the proposed theoretical framework*: Relying on theories on individual decision making from psychology, a conceptual framework is developed. It integrates a variety of behavioural factors potentially relevant for studying energy behaviour changes and is quantitatively studied, verified, and validated using the survey data.

- *Heterogeneity*: The quantitative assessment in this dissertation goes beyond aggregates and examines nine different actions and their dependence on both socioeconomic and behavioural characteristics of households as well as on structural dwelling factors, acknowledging the fact that various socioeconomic groups may exhibit different behavioural traits for different actions.

- *Statistical and econometric analysis*: This dissertation quantitatively estimates how behavioural factors in combination with socioeconomic characteristics of households and structural attributes of dwellings may trigger or inhibit the nine types of decisions by employing the probit model and analysis.

- *Comparative analysis*: The two countries in the sample permits me to compare households' choices and the role of behavioural factors across contexts. It allows testing whether behavioural factors included in the theoretical framework matter in different cases, strengthening their validity. Moreover, by making a comparison across countries, one could account for institutional, cultural, and climatic factors that do affect households' choices but are often challenging to capture explicitly.

***Empirical agent-based models*:** In this dissertation, a novel decision-making tool is developed to support policy decisions on climate change mitigation. For the first time, an agent-based model takes into account explicitly the behavioural heterogeneity in individual energy choices supported by survey data in two countries. Much attention is paid to the importance of individual energy behavioural change and social dynamics in climate change mitigation by developing an empirical regional decision-support tool (Chapters 3 and 4). Its innovative contribution to the literature is threefold:

- *From equilibrium to out-of-equilibrium model*: The current decision-making frameworks and tools available to policymakers address a broad range of policy issues, assuming that economic agents form a representative group(s), have perfect access to information, and adapt instantly and rationality to new situations. However, in reality, people make decisions driven by their diverse preferences, as shaped by socioeconomic conditions, behavioural biases, and social peer influences. This thesis went beyond classical economic models and the stylized representation of a perfectly informed optimizer. Firstly, I extend individual energy demand modelling based on economic factors alone by accounting explicitly for potential behavioural drivers and barriers in a formal model. A simulation method (*BENCH* model) is introduced; it allows one to aggregate individual behavioural and economic heterogeneity and captures dynamics in the aggregated regional trends by looking beyond a snapshot of a survey.
- *Theoretically and empirically grounded models*: The individual agents in the *BENCH* model change their energy use decisions following a

cognitive process inspired by psychological theories. In terms of environmental- and energy-related choices, three behavioural change theories are commonly applied: theory of planned behaviour (TPB), norm activation theory (NAT), and value–belief–norm (VBN) theory. Based on these theories, I developed a framework which supports the cognitive process of individuals' energy decision-making in the *BENCH* model. The *BENCH* model is calibrated based on our empirical data set.

- *From learning to behavioural scenarios*: Individuals in the *BENCH* ABM can adapt future choices by learning from their own experience and through their interactions with other individuals. I designed and ran several behavioural scenarios in *BENCH* ABM by differentiating the intensity of social interactions and the speed of learning, assuming an information policy (e.g., social advertising and promotion of pro-environmental behaviour). I estimated the macroeconomic impacts of energy behavioral changes of individual households by comparing these behavioural scenarios and conventional and price-based policies

To conclude, this research contributes uniquely to the growing body of literature on ABMs by focusing on the multi-step representation of individual behavioural change based on theoretically and empirically grounded agent rules.

***Novel systematic upscaling method*:** We investigate a systematic way to scale-up the individual energy behavioural change that combines the strengths of ABMs and CGE models to trace the macroeconomic and cross-sectoral impacts and indirect effects. The originality of this work is twofold:

- *Unique method*: During the last 20 years, CGE models have been used as standard tools for quantitative policy assessments. These models rely on advancements in microeconomic theory that represent the aggregate behaviour of main economic agents and interactions between them via supply-chain and trade links. To be able to analyse the macroeconomic and sectoral impacts of behavioural changes, CGE models can rely on complimentary modeling tools, such as AMBs. I employed the strengths of the ABM to capture and aggregate behavioural changes, social interactions, and learning and, on the strength of CGE models, to trace cross-sectoral impacts and indirect effects. ABM and CGE models each have their own assumptions, strengths, and weaknesses. We attempt to overcome the latter by linking the two types of models. To the best of my knowledge, this is the very first attempt to link empirical ABM and CGE models to estimate the macroeconomic impacts of individual energy behavioural changes.

- *Unique, rich datasets*: In addition to the household survey, which was designed and conducted to support this research, I wrote a research proposal and successfully obtained access to Eurostat households' microdata sets. These rich datasets gave me the opportunity to start bottom-up simulation modeling of household energy choices and integrate them further into a macroeconomic model. Therefore, I traced equilibrium, as well as out-of-equilibrium dynamics, by linking *BENCH* ABM and *EU-EMS* CGE models.

6.4. Policy and societal implications

The theoretically and empirically grounded modelling tools, such as the *BENCH* model, can serve as useful instruments with which to quantify regional impacts of qualitative and untraceable individual behavioural aspects. Understanding the cumulative impacts of behavioural processes and the effects of policies on different socioeconomic consumer groups in an artificial regional economy can help in participatory experiments. The model can serve as a simulation platform to support the engagement of stakeholders. It offers policymakers ways to explore various policy mixes combining price instruments (subsidies and taxes) with various targeted information policies to amplify the positive effect of individual behavioural changes regarding energy use. The insights delivered by this dissertation bring attention to a number of policy and societal implications:

***Behaviour matters*:** Human consumption, in combination with a growing population, contribute to climate change by increasing the rate of GHG emissions (Dietz and Rosa, 1997; Dietz et al., 2007; IPCC, 2014b). Over the last decade, instigated by the Paris agreement, the efforts to limit global warming have been expanding. However, significant attention is being devoted to new energy technologies on both the production and consumption sides, while changes in individual behaviour and management practices as part of the mitigation strategy are often neglected (Creutzig et al., 2018a). Within this dissertation, I brought attention to the role of individual behaviors by assessing their macroeconomic impacts in the transition to a low-carbon economy. The understanding of how bottom-up processes can impact climate mitigation guides us to effective development and implementation of policies.

***Heterogeneity is the key*:** In reality, people make decisions driven by their diverse preferences, which are shaped by socio-economic conditions, behavioural biases, and social peer influences (Farmer and Foley, 2009). Therefore, effective policymaking requires decision-supporting tools that can explore the interplay between economic decision-making and behavioural heterogeneity in households' energy choices when testing climate mitigation policies. Within this dissertation, I applied the *BENCH* ABM to shed light on the effects of individual decisions on climate change mitigation. The model with household heterogeneity in socio-demographic, dwelling, and behavioural factors shows rich dynamics and provides a more realistic image of socioeconomics by simulating an economy accounting for the social interactions of heterogeneous households. In Chapter 2, by employing a probit regression model and analysis, I quantitatively estimated how behavioural factors, in combination with socioeconomic characteristics of households and structural attributes of dwellings, can trigger or inhibit individual decisions. Analysis of sociodemographic factors highlighted the role of education in household energy-related decisions, particularly in energy investments and in switching to green- energy sources. Educated households are more active in improving their energy efficiency in both case studies. A higher level of education enables more insight, knowledge, and awareness of environmental, climate, and energy issues, which all, consequently, affect personal norms and lead to behaviour changes. Among dwelling characteristics, the type, size, and age of the residence have a strong influence on energy investments and conservation in both case studies. As expected, people living in houses are more eager to pursue large investments and have extra incentives to save energy by turning down the heater/air conditioner compared to people living in apartments. In Chapter 3, our simulation and analysis demonstrated that the two wealthiest household groups – from 90,000 to 110,000 or more euros per year – are lagging behind in making useful energy-related decisions. It may have to do with the fact that a wealthy household lifestyle creates a norm for energy-intensive behaviour. The pioneers are the first three bottom-income groups: contributing 91% and 93% cumulatively in 2020 and 2030, respectively. The households in the second income group (10,000-30,000 euros per year) contribute more than 50% of this energy-related effort. Moreover, I explored the heterogeneity among behavioural factors (e.g., knowledge, awareness, and personal and social norms), and the results showed that they play at least as important a role as monetary factors, such as income.

***Social norms are essential*:** Social norms have an essential role in shaping personal norms. Households are not making decisions in isolation, as they are prone to being influenced by peers in their social networks and local communities. A group benefits from certain individual actions, but no individual has sufficient incentive to act alone. Together, personal and social norms can trigger individuals to make energy-efficient decisions. In addition, the impact of the societal and institutional rules – culture, fiscal rules, and regulations – on individuals is inevitable, as confirmed by our case studies.

***One region affects other regions*:** By scaling up individual energy choices to the EU level, the other side effects of the cumulative impact of individual behaviour changes are discovered (Chapter 5). The transition to a low-carbon economy varies from one region to another, and one single region could affect another region(s). Some regions lag behind and some move ahead due to heterogeneity in individuals' sociodemographic (e.g., education and age), structural characteristics (e.g., type and size of dwellings), behavioural and social traits, and spatial characteristics (e.g., urban vs. rural).

***Policy as a package (set of policies)*:** As discussed earlier, individuals are more than just consumers in climate change mitigation. Therefore, climate mitigation policies should go beyond economic cost-benefit incentives (e.g., subsidies and taxes). Firstly, the social environment, cultural practices, public knowledge, producer technologies and services, and facilities used by consumers should all be considered when designing implementable and politically feasible policy options. Secondly, various financial, social, and other instruments in the policy mix should be designed as a coherent set to reinforce each other, optimizing their joint effectiveness. In particular, policies, such as the provision of targeted information, social advertisements, and power of celebrities for the broader public in combination with education, can be used to create more knowledge and awareness in the longer run and could accompany and reinforce the effectiveness of other stimuli, such as subsidies. These types of policies (soft policies) may prove to be more effective in promoting green-energy solutions implemented by households compared to fiscal policy measures alone.

To conclude, this dissertation suggests a policy package as an essential strategy for climate change mitigation. Such a package could combine the following policies: (a) short-term, conventional, price-based policies (e.g., carbon price, taxes); (b) nudging and soft policies (e.g., education, information dissemination); and (c) unbounded regional-to-global policies (e.g., based on NSDS, SDGs), of which the latter two could be considered (semi-) long-term strategies.

6.5. Outlook to future work

As this research focuses on the residential demand side, much attention is paid to the importance of individual energy behavioural change and social dynamics in climate change mitigation. The macroeconomic and cross-sectoral impacts and indirect effects of individual energy behavioural change are estimated through an original, bottom-up, soft-link method. The future work can go in two main directions: advancing the modelling and exploring the philosophy and ethics of climate change.

From the *modelling perspective*, further research is needed on: (1) Integrating this behaviourally rich demand-side modelling with the dynamics of dwelling stock. Static and aging housing should be replaced by scenarios of structural and technological progress in new urban development (e.g., zero-carbon-footprint buildings) and refurbishing old housing stock in cities. (2) Improve modelling and analysis of dynamics of institutions and collective action (e.g.

local initiatives). (3) Furthermore, the agent-based model could benefit from improved modelling and analyses of the energy supply side to assure market feedbacks (Tesfatsion, 2018).This will also allow detailed endogenous modeling of various energy sources and technological learning. (4) Linking to transport model may be another interesting direction for future research. For example, household energy demand is expected to change due to the penetration of electric vehicles and self-driving public and private transport. (5) While this thesis presents a soft link between the two models (ABM and CGE), ideally, one should pursue a two-way, dynamic integration (hard-link) in which the two empirical models would be linked using software wrappers and modern web interfaces for integration (Belete et al., 2018). (6) Large number of parameters and multidimensionality of the generated data in ABMs, are a challenge in further exploring and understating results (Lee et al., 2015). Combining exploratory analysis (Kwakkel and Jaxa-Rozen, 2016; Kwakkel and Pruyt, 2013; Premo, 2006)and data mining techniques to understand the model's behaviour and its sensitivity to initial configurations of its parameters would be an interesting topic to explore in the future. From *the philosophical and ethical perspective*, researchers could focus on how climate change impacts values and norms (Nyborg et al., 2016). Importantly, any action on climate change challenges ethical issues of responsibility across individuals, nations, and generations (Gardiner and Hartzell-Nichols, 2012).

Bibliography

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.

Abrahamse, W., Steg, L. (2009) How do socio-demographic and psychological factors relate to households' direct and indirect energy use and savings? Journal of Economic Psychology 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. Human Ecology Review 18, 30-40.

Acemoglu, D., Ozdaglar, A. (2011) Opinion Dynamics and Learning in Social Networks. Dynamic Games and Applications 1, 3-49.

Adnan, N., Md Nordin, S., Hadi Amini, M., Langove, N. (2018) What make consumer sign up to PHEVs? Predicting Malaysian consumer behavior in adoption of PHEVs. Transportation Research Part A: Policy and Practice 113, 259-278.

Adnan, N., Nordin, S.M., Rahman, I., Amini, M.H. (2017) A market modeling review study on predicting Malaysian consumer behavior towards widespread adoption of PHEV/EV. Environmental Science and Pollution Research 24, 17955-17975.

Adnana, N., Nordina, S.M., Rahmanb, I. (2017) Adoption of PHEV/EV in Malaysia: A critical review on predicting consumer behaviour. Renewable and Sustainable Energy Reviews 72.

Ajzen, I. (1980a) Understanding attitudes and predicting social behavior. Prentice-Hall;, Englewood Cliffs, N.J.

Ajzen, I. (1980b) Understanding Events - Affect and the Construction of Social-Action - Heise,Dr. Contemporary Psychology 25, 775-776.

Al Mamun, A., Mohamad, M.R., Yaacob, M.R.B., Mohiuddin, M. (2018) Intention and behavior towards green consumption among low-income households. Journal of Environmental Management 227, 73-86.

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

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. Environmental Research Letters 10.

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.

Anderson, K., Le Quere, C., Mclachlan, C. (2014) Radical emission reductions: the role of demand reductions in accelerating full decarbonization. Carbon Management 5, 321-323.

Armitage, C.J., Conner, M. (2001) Efficacy of the theory of planned behaviour: A meta-analytic review. British Journal of Social Psychology 40, 471-499.

Arthur, W.B., (2006) Chapter 32 Out-of-Equilibrium Economics and Agent-Based Modeling, in: Tesfatsion, L., Judd, K.L. (Eds.), Handbook of Computational Economics. Elsevier, pp. 1551-1564.

Axtell, R., Guerrero, O. (forthcoming 2018) Dynamics of Firms from the Bottom Up: Data, Theories and Models. MIT Press.

Babatunde, K.A., Begum, R.A., Said, F.F. (2017) Application of computable general equilibrium (CGE) to climate change mitigation policy: A systematic review. Renewable and Sustainable Energy Reviews 78, 61-71.

Baiocchi, G., Minx, J., Hubacek, K. (2010) The Impact of Social Factors and Consumer Behavior on Carbon Dioxide Emissions in the United Kingdom. Journal of Industrial Ecology 14, 50-72.

Bamberg, S., Hunecke, M., Blobaum, A. (2007) Social context, personal norms and the use of public transportation: Two field studies. Journal of Environmental Psychology 27, 190-203.

Bamberg, S., Moser, G. (2007) Twenty years after Hines, Hungerford, and Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour. Journal of Environmental Psychology 27, 14-25.

Bamberg, S., Rees, J., Seebauer, S. (2015) Collective climate action: Determinants of participation intention in community-based pro-environmental initiatives. Journal of Environmental Psychology 43, 155-165.

Bao, L., Fritchman, J.C. (2018) Information of Complex Systems and Applications in Agent Based Modeling. Scientific Reports 8, 6177.

Barros, G. (2010) Herbert A. Simon and the concept of rationality: boundaries and procedures. Brazilian Journal of Political Economy 30, 455-472.

Bator, R.J., Tabanico, J.J., Walton, M.L., Schultz, P.W. (2014) Promoting energy conservation with implied norms and explicit messages. Social Influence 9, 69-82.

Belete, G., Voinov, A., Bulavskaya, T., Niamir, L., Dhavala, K., Arto, I., Moghayer, S., Filatova, T. (2018) Web service based approach to linking heterogeneous climate-energy-economy models for climate change mitigation analysis. Applied Energy Under review

Berger, T., Schreinemachers, P. (2006) Creating agents and landscapes for multiagent systems from random samples. Ecology and Society 11.

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, 4th European Conference on Behaviour and Energy Efficiency, Coimbra, Portugal.

Bin, S., Dowlatabadi, H. (2005) Consumer lifestyle approach to US energy use and the related CO2 emissions. Energy Policy 33, 197-208.

Botetzagias, I., Malesios, C., Poulou, D. (2014) Electricity curtailment behaviors in Greek households: Different behaviors, different predictors. Energy Policy 69, 415-424.

Bravo, G., Vallino, E., Cerutti, A.K., Pairotti, M.B. (2013) Alternative scenarios of green consumption in Italy: An empirically grounded model. Environmental Modelling & Software 47, 225-234.

Bressers, H., Ligteringen, J.J. (2007) Political-administrative policies for sustainable household behavior. International Journal of Environmental Consumerism 2, 5-15.

Brown, D.G., Robinson, D.T. (2006) Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl. Ecology and Society 11.

Buchanan, D.A., Huczynski, A. (2016) Organizational behaviour, Ninth edition. ed. Pearson, Harlow, England ; New York.

Buchanan, K., Banks, N., Preston, I., Russo, R. (2016) The British public's perception of the UK smart metering initiative: Threats and opportunities. Energy Policy 91, 87-97.

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

Cabeza, L.F., Ürge-Vorsatz, D., Ürge, D., Palacios, A., Barreneche, C. (2018) Household appliances penetration and ownership trends in residential buildings. Renewable and Sustainable Energy Reviews 98, 1-8.

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.

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

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., Afman, M.R. (2013) An agent-based model of transitions in consumer lighting: Policy impacts from the E.U. phase-out of incandescents. Environmental Innovation and Societal Transitions 7.

Chappin, E., Dijkema, G., van Dam, K., Lukszo, Z. (2007) Modeling strategic and operational decision-making - An agent-based model of electricity producers. European Simulation and Modelling Conference 2007, 356-363.

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.

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.

Cooper, B. (2017) What drives compliance? An application of the theory of planned behaviour to urban water restrictions using structural equation modelling. Applied Economics 49, 1426-1439.

Crespo Cuaresma, J. (2017) Income projections for climate change research: A framework based on human capital dynamics. Global Environmental Change 42, 226-236.

Creutzig, F., Fernandez, B., Haberl, H., Khosla, R., Mulugetta, Y., Seto, K.C. (2016) Beyond Technology: Demand-Side Solutions for Climate Change Mitigation. Annual Review of Environment and Resources, Vol 41 41, 173-198.

Creutzig, F., Roy, J., Lamb, W.F., Azevedo, I.M.L., Bruine de Bruin, W., Dalkmann, H., Edelenbosch, O.Y., Geels, F.W., Grubler, A., Hepburn, C., Hertwich, E.G., Khosla, R., Mattauch, L., Minx, J.C., Ramakrishnan, A., Rao, N.D., Steinberger, J.K., Tavoni, M., Ürge-Vorsatz, D., Weber, E.U. (2018a) Towards demand-side solutions for mitigating climate change. Nature Climate Change 8, 268-271.

Creutzig, F., Roy, J., Lamb, W.F., Azevedo, I.M.L., de Bruin, W.B., Dalkmann, H., Edelenbosch, O.Y., Geels, F.W., Grubler, A., Hepburn, C., Hertwich, E.G., Khosla, R., Mattauch, L., Minx, J.C., Ramakrishnan, A., Rao, N.D., Steinberger, J.K., Tavoni, M., Urge-Vorsatz, D., Weber, E.U. (2018b) Towards demand-side solutions for mitigating climate change. Nature Climate Change 8, 268-271.

Davis, L.W. (2010) Evaluating the Slow Adoption of Energy Efficient Investments: Are Renters Less Likely to Have Energy Efficient Appliances? National Bureau of Economic Research Working Paper Series No. 16114.

De Groot, J.I.M., Steg, L. (2009) Morality and Prosocial Behavior: The Role of Awareness, Responsibility, and Norms in the Norm Activation Model. Journal of Social Psychology 149, 425-449.

Degroot, M.H. (1974) Reaching a Consensus. Journal of the American Statistical Association 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. Renewable and Sustainable Energy Reviews 11, 1498-1513.

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

Desa, A., Kadir, N.B.y.A., Yusooff, F. (2011) A Study on the Knowledge, Attitudes, Awareness Status and Behaviour Concerning Solid Waste Management. Procedia - Social and Behavioral Sciences 18, 643-648.

Di Falco, S., Sharma, S. (2018) Investing in Climate Change Adaptation: Motivations and Green Incentives in the Fiji Islands. Ecological Economics 154, 394-408.

Dietz, T., Rosa, E.A. (1997) Effects of population and affluence on CO₂ emissions. Proceedings of the National Academy of Sciences 94, 175-179.

Dietz, T., Rosa, E.A., York, R. (2007) Driving the human ecological footprint. Frontiers in Ecology and the Environment 5, 13-18.

Dietz, T., Stern, P.C., Weber, E.U. (2013) Reducing Carbon-Based Energy Consumption through Changes in Household Behavior. Daedalus 142, 78-89.

Donaldson, S.I., Grant-Vallone, E.J. (2002) Understanding Self-Report Bias in Organizational Behavior Research. Journal of Business and Psychology 17, 245-260.

Doppelt, B., Markowitz, E.M., (2009) Reducing Greenhouse Gas Emissions through Behavioral Change : An Assessment of Past Research On Energy Use, Transportation and Water Consumption, in: Institute for a Sustainable Environment, U.o.O. (Ed.), p. 17.

Du, H., Liu, D., Sovacool, B.K., Wang, Y., Ma, S., Li, R.Y.M. (2018) Who buys New Energy Vehicles in China? Assessing social-psychological predictors of purchasing awareness, intention, and policy. Transportation Research Part F: Traffic Psychology and Behaviour 58, 56-69.

Ebeling, F., Lotz, S. (2015) Domestic uptake of green energy promoted by opt-out tariffs. Nature Climate Change 5, 868-+.

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.

Fagiolo, G., Roventini, A. (2017) Macroeconomic Policy in DSGE and Agent-Based Models Redux: New Developments and Challenges Ahead. Journal of Artificial Societies and Social Simulation 20, 1.

Faiers, A., Neame, C. (2006) Consumer attitudes towards domestic solar power systems. Energy Policy 34, 1797-1806.

Farmer, J.D., Foley, D. (2009) The economy needs agent-based modelling. Nature 460, 685-686.

Farmer, J.D., Hepburn, C., Mealy, P., Teytelboym, A. (2015) A Third Wave in the Economics of Climate Change. Environmental & Resource Economics 62, 329-357.

Federico, G., Vives, X. (2008) Competition and regulation in the spanish gas and electiricity markets. Public-Ptivate Sector Research Center, IESE Bussiness School, Madrid, Spain

Filatova, T., Moghayer, S.M., Arto, I., Belete, G., Dhavala, K., Hasselmann, K., Ivanova, O., Kovalevsky, D., Naimir, L., Voinov, A., (2014) Dynamics of climate-energy-economy systems: development of a methodological framework for an integrated system of models.

Filatova, T., Niamir, L., (2018) Changing climate – changing behavior: empirical agent based computational models for climate change economics, in: Lamperti, F., Monasterolo, I., Roventini, A. (Eds.), Complexity and Climate Change: An Evolutionary Political Economy Approach. Taylor & Francis.

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.

Filatova, T., Verburg, P.H., Parker, D.C., Stannard, C.A. (2013) Spatial agent-based models for socio-ecological systems: Challenges and prospects. Environmental Modelling & Software 45, 1-7.

Frederiks, E.R., Stennerl, K., Hobman, E.V. (2015) Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. Renewable & Sustainable Energy Reviews 41, 1385-1394.

Fricko, O., Havlik, P., Rogelj, J., Klimont, Z., Gusti, M., Johnson, N., Kolp, P., Strubegger, M., Valin, H., Amann, M., Ermolieva, T., Forsell, N., Herrero, M., Heyes, C., Kindermann, G., Krey, V., McCollum, D.L., Obersteiner, M., Pachauri, S., Rao, S., Schmid, E., Schoepp, W., Riahi, K. (2017) The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century. Global Environmental Change 42, 251-267.

Fujimori, S., Hasegawa, T., Masui, T., Takahashi, K., Herran, D.S., Dai, H., Hijioka, Y., Kainuma, M. (2017) SSP3: AIM implementation of Shared Socioeconomic Pathways. Global Environmental Change 42, 268-283.

Gadenne, D., Sharma, B., Kerr, D., Smith, T. (2011) The influence of consumers' environmental beliefs and attitudes on energy saving behaviours. Energy Policy 39, 7684-7694.

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

Gao, L., Wang, S., Li, J., Li, H. (2017) Application of the extended theory of planned behavior to understand individual's energy saving behavior in workplaces. Resources, Conservation and Recycling 127, 107-113.

Gardiner, S.M., Hartzell-Nichols, L. (2012) Ethics and Global Climate Change. Nature Education Knowledge 3, 5.

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. Environmental Modelling & Software 44, 62-75.

Ghorbani, A., Bravo, G. (2016) Managing the commons: A simple model of the emergence of institutions through collective action. International Journal of the Commons 10, 200-219.

Gilbert, G.N. (2008) Agent-based models. Sage Publications, Los Angeles.

Gilbert, G.N. (2010) Computational Social Science. SAGE, Los Angeles.

Gillingham, K., Harding, M., Rapson, D. (2012) Split Incentives in Residential Energy Consumption. The Energy Journal 33.

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.

Gotts, N.M., Polhill, J.G. (2009) When and How to Imitate Your Neighbours: Lessons from and for FEARLUS. Jasss-the Journal of Artificial Societies and Social Simulation 12.

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.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S.K., Huse, G., Huth, A., Jepsen, J.U., Jorgensen, C., Mooij, W.M., Muller, B., Pe'er, G., Piou, C., Railsback, S.F., Robbins, A.M., Robbins, M.M., Rossmanith, E., Ruger, N., Strand, E., Souissi, S., Stillman, R.A., Vabo, R., Visser, U., DeAngelis, D.L. (2006) A standard protocol for describing individual-based and agent-based models. Ecological Modelling 198, 115-126.

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. Environmental Modelling & Software 87, 39-48.

Grubler, A., Wilson, C., Bento, N., Boza-Kiss, B., Krey, V., McCollum, D.L., Rao, N.D., Riahi, K., Rogelj, J., De Stercke, S., Cullen, J., Frank, S., Fricko, O., Guo, F., Gidden, M., Havlik, P., Huppmann, D., Kiesewetter, G., Rafaj, P., Schoepp, W., Valin, H. (2018) A low energy demand scenario for meeting the 1.5 degrees C target and sustainable development goals without negative emission technologies. Nature Energy 3, 515-527.

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.

Ham, M., Jeger, M., Frajman Ivković, A. (2015) The role of subjective norms in forming the intention to purchase green food. Economic Research-Ekonomska Istraživanja 28, 738-748.

Hamilton, I.G., Steadman, P.J., Bruhns, H., Summerfield, A.J., Lowe, R. (2013) Energy efficiency in the British housing stock: Energy demand and the Homes Energy Efficiency Database. Energy Policy 60, 462-480.

Hao, F., Huang, W., Sloan, M.M. (2018) Environmental Concern in the United States and China: The Influence of Measurement in National Context. Social Currents 5, 479-493.

He, X., Reiner, D. (2017) Why consumers switch energy suppliers: The role of individual attitudes. Energy Journal 38, 25-53.

Hegselmann, R., Krause, U. (2002) Opinion Dynamics and Bounded Confidence, Models, Analysis and Simulation. Journal of Artificial Societies and Social Simulation 5.

Hertwich, E.G., Peters, G.P. (2009) Carbon Footprint of Nations: A Global, Trade-Linked Analysis. Environmental Science & Technology 43, 6414-6420.

Hess, A.K., Samuel, R., Burger, P. (2018) Informing a social practice theory framework with social-psychological factors for analyzing routinized energy consumption: A multivariate analysis of three practices. Energy Research and Social Science 46, 183-193.

Hong, L., Page, S.E. (2004) Groups of diverse problem solvers can outperform groups of high-ability problem solvers. Proceedings of the National Academy of Sciences of the United States of America 101, 16385-16389.

Humphreys, P., Imbert, C. (2012) Models, simulations, and representations. Routledge, New York.

Hunt, L.C., Evans, J. (2009) International handbook on the economics of energy. Edward Elgar, Cheltenham, UK ; Northampton, MA.

Hutchinson, E.J., Wilkinson, P., Hong, S.H., Oreszczyn, T. (2006) Can we improve the identification of cold homes for targeted home energy-efficiency improvements? Applied Energy 83, 1198-1209.

Imanina, N.H.N., Lu, T.K., Fadhilah, A.R., (2016) A proposed model of factors influencing hydrogen fuel cell vehicle acceptance, IOP Conference Series: Earth and Environmental Science, 1 ed.

IPCC, (2014a) Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, in: Pachauri, R.K., Meyer, L.A. (Eds.), Geneva, Switzerland, p. 151.

IPCC, (2014b) Fifth assessment report: Climate change.

Isley, S.C., Lempert, R.J., Popper, S.W., Vardavas, R. (2015) The effect of near-term policy choices on long-term greenhouse gas transformation pathways. Global Environmental Change 34, 147-158.

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. Applied 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.

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. Ecological Economics 35, 357-379.

Jensen, T., (2017) Simulating co-diffusion of innovations: Feedback technology & behavioral change, TU Delft Energy & Industry. TU Delft.

Jensen, T., Holtz, G., Baedeker, C., Chappin, E.J.L. (2016) Energy-efficiency impacts of an air-quality feedback device in residential buildings: An agent-based modeling assessment. Energy and Buildings 116, 151-163.

Jia, J.J., Xu, J.H., Fan, Y., Ji, Q. (2018) Willingness to accept energy-saving measures and adoption barriers in the residential sector: An empirical analysis in Beijing, China. Renewable and Sustainable Energy Reviews 95, 56-73.

Jiang, L., O'Neill, B.C. (2017) Global urbanization projections for the Shared Socioeconomic Pathways. Global Environmental Change 42, 193-199.

JRC, E. (2014) ETRI 2014 Energy Technology Reference Indicator projections for 2010-2050. European Commission JRC (Joint Research Centre).

Kaasa, A., Vadi, M., Varblane, U. (2016) A new dataset of cultural distances for European countries and regions. Research in International Business and Finance 37, 231-241.

Kahneman, D. (2003) A psychological perspective on economics. American Economic Review 93, 162-168.

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.

Kancs, A. (2001) Predicting European enlargement impacts - A framework of interregional general equilibrium. Eastern European Economics 39, 31-63.

Kar, A., Zerriffi, H. (2018) From cookstove acquisition to cooking transition: Framing the behavioural aspects of cookstove interventions. Energy Research and Social Science 42, 23-33.

Karatasou, S., Santamouris, M. (2010) Detection of low-dimensional chaos in buildings energy consumption time series. Communications in Nonlinear Science and Numerical Simulation 15, 1603-1612.

Katz, J., Kitzing, L., Schröder, S.T., Andersen, F.M., Morthorst, P.E., Stryg, M. (2018) Household electricity consumers' incentive to choose dynamic pricing under different taxation schemes. Wiley Interdisciplinary Reviews: Energy and Environment 7.

Kc, S., Lutz, W. (2017) The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100. Global Environmental Change 42, 181-192.

Kiesling, E., Gunther, M., Stummer, C., Wakolbinger, L.M. (2012) Agent-based simulation of innovation diffusion: a review. Central European Journal of Operations Research 20, 183-230.

Kobus, C.B.A., Klaassen, E.A.M., Mugge, R., Schoormans, J.P.L. (2015) A real-life assessment on the effect of smart appliances for shifting households' electricity demand. Applied Energy 147, 335-343.

Kotevska, A., Dimitrievski, D., Erjavec, E., (2013) PARTIAL EQUILIBRIUM MODEL AS A TOOL FOR POLICY ANALYSIS IN AGRICULTURE: AN EMPIRICAL EVIDENCE OF MACEDONIA, pp. 52-65.

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.

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

Krook-Riekkola, A., Berg, C., Ahlgren, E.O., Söderholm, P. (2017) Challenges in top-down and bottom-up soft-linking: Lessons from linking a Swedish energy system model with a CGE model. Energy 141, 803-817.

Kumar, S. (2016) Assessment of renewables for energy security and carbon mitigation in Southeast Asia: The case of Indonesia and Thailand. Applied Energy 163, 63-70.

Kuo, T.C., Tseng, M.L., Lin, C.H., Wang, R.W., Lee, C.H. (2018) Identifying sustainable behavior of energy consumers as a driver of design solutions: The missing link in eco-design. Journal of Cleaner Production 192, 486-495.

Kwakkel, J.H., Jaxa-Rozen, M. (2016) Improving scenario discovery for handling heterogeneous uncertainties and multinomial classified outcomes. Environmental Modelling & Software 79, 311-321.

Kwakkel, J.H., Pruyt, E. (2013) Exploratory Modeling and Analysis, an approach for model-based foresight under deep uncertainty. Technological Forecasting and Social Change 80, 419-431.

Lamperti, F., Mandel, A., Napoletano, M., Sapio, A., Roventini, A., Balint, T., Khorenzhenko, I. (2018) Towards agent-based integrated assessment models: examples, challenges, and future developments. Regional Environmental Change.

Latta, G.S., Sjølie, H.K., Solberg, B. (2013) A review of recent developments and applications of partial equilibrium models of the forest sector. Journal of Forest Economics 19, 350-360.

Le Quere, C., Andrew, R.M., Friedlingstein, P., Sitch, S., Pongratz, J., Manning, A.C., Korsbakken, J.I., Peters, G.P., Canadell, J.G., Jackson, R.B., Boden, T.A., Tans, P.P., Andrews, O.D., Arora, V.K., Bakker, D.C.E., Barbero, L., Becker, M., Betts, R.A., Bopp, L., Chevallier, F., Chini, L.P., Ciais, P., Cosca, C.E., Cross, J., Currie, K., Gasser, T., Harris, I., Hauck, J., Haverd, V., Houghton, R.A., Hunt, C.W., Hurtt, G., Ilyina, T., Jain, A.K., Kato, E., Kautz, M., Keeling, R.F., Goldewijk, K.K., Kortzinger, A., Landschutzer, P., Lefevre, N., Lenton, A., Lienert, S., Lima, I., Lombardozzi, D., Metzl, N., Millero, F., Monteiro, P.M.S., Munro, D.R., Nabel, J.E.M.S., Nakaoka, S., Nojiri, Y., Padin, X.A., Peregon, A., Pfeil, B., Pierrot, D., Poulter, B., Rehder, G., Reimer, J., Rodenbeck, C., Schwinger, J., Seferian, R., Skjelvan, I., Stocker, B.D., Tian, H.Q., Tilbrook, B., Tubiello, F.N., van der Laan-Luijkx, I.T., van der Werf, G.R., van Heuven, S., Viovy, N., Vuichard, N., Walker, A.P., Watson, A.J., Wiltshire, A.J., Zaehle, S., Zhu, D. (2018) Global Carbon Budget 2017. Earth System Science Data 10, 405-448.

LeBaron, B., (2006) Chapter 24 Agent-based Computational Finance, in: Tesfatsion, L., Judd, K.L. (Eds.), Handbook of Computational Economics. Elsevier, pp. 1187-1233.

LeBaron, B., Tesfatsion, L. (2008) Modeling Macroeconomies as Open-Ended Dynamic Systems of Interacting Agents. American Economic Review 98, 246-250.

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. Journal of Artificial Societies and Social Simulation 18, 4.

Li, R., Dane, G., Finck, C., Zeiler, W. (2017) Are building users prepared for energy flexible buildings?—A large-scale survey in the Netherlands. Applied Energy 203, 623-634.

Li, Z., Hu, B. (2018) Perceived health risk, environmental knowledge, and contingent valuation for improving air quality: New evidence from the Jinchuan mining area in China. Economics and Human Biology 31, 54-68.

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.

Liu, Y., Sheng, H., Mundorf, N., Redding, C., Ye, Y. (2017) Integrating norm activation model and theory of planned behavior to understand sustainable transport behavior: Evidence from China. International Journal of Environmental Research and Public Health 14.

Long, C., Mills, B.F., Schleich, J. (2018) Characteristics or culture? Determinants of household energy use behavior in Germany and the USA. Energy Efficiency 11, 777-798.

Mahapatra, K., Gustavsson, L. (2008) An adopter-centric approach to analyze the diffusion patterns of innovative residential heating systems in Sweden. Energy Policy 36, 577-590.

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.

Matsui, K., Ochiai, H., Yamagata, Y. (2014) Feedback on electricity usage for home energy management: A social experiment in a local village of cold region. Applied Energy 120, 159-168.

Matthies, E., Kastner, I., Klesse, A., Wagner, H.J. (2011) High reduction potentials for energy user behavior in public buildings: How much can psychology-based interventions achieve? Journal of Environmental Studies and Sciences 1, 241-255.

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

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

Melnikov, N.B., O'Neill, B.C., Dalton, M.G., van Ruijven, B.J. (2017) Downscaling heterogeneous household outcomes in dynamic CGE models for energy-economic analysis. Energy Economics 65, 87-97.

Michelsen, C.C., Madlener, R. (2012) Homeowners ' preferences for adopting innovative residential heating systems: A discrete choice analysis for Germany. Energy Economics 34, 1271-1283.

Mills, B., Schleich, J. (2010) What's driving energy efficient appliance label awareness and purchase propensity? Energy Policy 38, 814-825.

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

Mills, B.F., Schleich, J. (2009) Profits or preferences? Assessing the adoption of residential solar thermal technologies. Energy Policy 37, 4145-4154.

Mohandes, N., Sanfilippo, A., Al Fakhri, M. (2019) Modeling residential adoption of solar energy in the Arabian Gulf Region. Renewable Energy 131, 381-389.

Moussaid, M., Brighton, H., Gaissmaier, W. (2015) The amplification of risk in experimental diffusion chains. Proceedings of the National Academy of Sciences of the United States of America 112, 5631-5636.

Nakano, R., Zusman, E., Nugroho, S., Kaswanto, R.L., Arifin, N., Munandar, A., Arifin, H.S., Muchtar, M., Gomi, K., Fujita, T. (2018) Determinants of energy savings in Indonesia: The case of LED lighting in Bogor. Sustainable Cities and Society 42, 184-193.

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

Niamir, L., Filatova, T., (2016) From Climate Change Awareness to Energy Efficient Behaviour, 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.

Niamir, L., Filatova, T., Ivanova, O., Voinov, A., Bressers, H., (2018a) Transition to Low-carbon Society: A Framework to Understand Household Energy-efficient Behavioural Change, 5th European Conference on Behaviour and Energy Efficiency, Zurich, Switzerland

Niamir, L., Filatova, T., Voinov, A., Bressers, H., (2017) Household energy use and behavior change tracking framework: From data to simulation, Conference on Complex Systems, Cancun, Mexico.

Niamir, L., Filatova, T., Voinov, A., Bressers, H. (2018b) Transition to low-carbon economy: Assessing cumulative impacts of individual behavioral changes. Energy Policy 118, 325-345.

Niamir, L., Ivanova, O., Filatova, T., Voinov, A., (2018c) Tracing Macroeconomic Impacts of Individual Behavioral Changes through Model Integration, 1st IFAC Workshop on Integrated Assessment Modelling for Environmental Systems, Brescia, Italy.

Niamir, L., Ivanova, O., T., F., Voinov, A., Bressers, H. (2018d) Demand-side solutions for climate change mitigation: bottom up drivers of household energy behavior change. Applied Energy Under review

Niamir, L., Kiesewetter, G., Wagner, F., Schöpp, W., Filatova, T., Voinov, A., Bressers, H. (2018e) Assessing the macroeconomic impacts of individuals energy-efficient behavior on upstream carbon emissions. Climatic Change Under review.

Nordlund, A., Jansson, J., Westin, K. (2018) Acceptability of electric vehicle aimed measures: Effects of norm activation, perceived justice and effectiveness. Transportation Research Part A: Policy and Practice 117, 205-213.

Nordlund, A.M., Garvill, J. (2003) Effects of values, problem awareness, and personal norm on willingness to reduce personal car use. Journal of Environmental Psychology 23, 339-347.

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.

Olsson, L.E., Huck, J., Friman, M. (2018) Intention for car use reduction: Applying a stage-based model. International Journal of Environmental Research and Public Health 15.

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. Journal of Economic Psychology 39, 141-153.

Oreskes, N. (2004) The Scientific Consensus on Climate Change. Science 306, 1686-1686.

Ostrom, E. (2006) The value-added of laboratory experiments for the study of institutions and common-pool resources. Journal of Economic Behavior and Organization 61, 149-163.

Ostrom, E. (2007) A diagnostic approach for going beyond panaceas. Proceedings of the National Academy of Sciences 104, 15181-15187.

Palmer, J., Sorda, G., Madlener, R. (2015) Modeling the diffusion of residential photovoltaic systems in Italy: An agent-based simulation. Technological Forecasting and Social Change 99, 106-131.

Park, E., Kwon, S.J. (2017) What motivations drive sustainable energy-saving behavior?: An examination in South Korea. Renewable and Sustainable Energy Reviews 79, 494-502.

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. Annals of the Association of American Geographers 93, 314-337.

Parris, B., (2005) Trade and Industrial Policy in Developing Countries: What Scope for Interfaces between Agent-Based Models and Computable-General Equilibrium Models?, in: University, B. (Ed.), Paper submitted for international workshop on agent-based models for economic policy design.

Peters, G.P., Le Quéré, C., Andrew, R.M., Canadell, J.G., Friedlingstein, P., Ilyina, T., Jackson, R.B., Joos, F., Korsbakken, J.I., McKinley, G.A., Sitch, S., Tans, P. (2017) Towards real-time verification of CO2 emissions. Nature Climate Change 7, 848-850.

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, pp. 341-354.

Polhill, J.G., Gotts, N.M. (2009) Ontologies for transparent integrated human-natural system modelling. Landscape Ecology 24, 1255-1267.

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. Environment and Behavior 36, 70-93.

Premo, L.S., (2006) Exploratory agent-based models: Towards an experimental ethnoarchaeology, in: Clark, J.T., Hagemeister, E.M. (Eds.), Digital discovery: Exploring new frontiers in human heritage. Archeolingua Press, Budapest.

Raaij, W.F., (2017) Social psychology and economic behaviour: Heuristics and biases in decision making and judgement, in: Steg, L., Keizer, K., Buunk, A.P., Rothengatter, T. (Eds.), Applied social psychology. Cambridge University Press.

Rai, V., Henry, A.D. (2016) Agent-based modelling of consumer energy choices. Nature Climate 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. Environmental Modelling & Software 70, 163-177.

Raihanian Mashhadi, A., Behdad, S. (2017) Environmental Impact Assessment of the Heterogeneity in Consumers' Usage Behavior: An Agent-Based Modeling Approach. Journal of Industrial Ecology.

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

Rao, S., Klimont, Z., Smith, S.J., Van Dingenen, R., Dentener, F., Bouwman, L., Riahi, K., Amann, M., Bodirsky, B.L., van Vuuren, D.P., Aleluia Reis, L., Calvin, K., Drouet, L., Fricko, O., Fujimori, S., Gernaat, D., Havlik, P., Harmsen, M., Hasegawa, T., Heyes, C., Hilaire, J., Luderer, G., Masui, T., Stehfest, E., Strefler, J., van der Sluis, S., Tavoni, M. (2017) Future air pollution in the Shared Socio-economic Pathways. Global Environmental Change 42, 346-358.

Richiardi, M., Leombruni, R., Saam, N.J., Sonnessa, M. (2006) A Common Protocol for Agent-Based Social Simulation. Journal of Artificial Societies and Social Simulation 9.

Rive, N., Torvanger, A., Fuglestvedt, J.S. (2006) Climate agreements based on responsibility for global warming: Periodic updating, policy choices, and regional costs. Global Environmental Change 16, 182-194.

Rogers, E.M. (2003) Diffusion of innovations, 5th ed. Free Press, New York.

Rommel, J., Sagebiel, J., Müller, J.R. (2016) Quality uncertainty and the market for renewable energy: Evidence from German consumers. Renewable Energy 94, 106-113.

Rosenow, J., Guertler, P., Sorrell, S., Eyre, N. (2018) The remaining potential for energy savings in UK households. Energy Policy 121, 542-552.

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.

Safarzyńska, K., Brouwer, R., Hofkes, M. (2013) Evolutionary modelling of the macro-economic impacts of catastrophic flood events. Ecological Economics 88, 108-118.

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

Sardianou, E., Genoudi, P. (2013) Which factors affect the willingness of consumers to adopt renewable energies? Renewable Energy 57, 1-4.

Sarkis, A.M. (2017) A comparative study of theoretical behaviour change models predicting empirical evidence for residential energy conservation behaviours. Journal of Cleaner Production 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.

Schwarz, N., Ernst, A. (2009) Agent-based modeling of the diffusion of environmental innovations - An empirical approach. Technological Forecasting and Social Change 76, 497-511.

Seebauer, S. (2018) The psychology of rebound effects: Explaining energy efficiency rebound behaviours with electric vehicles and building insulation in Austria. Energy Research and Social Science 46, 311-320.

Shin, D.W., McCann, L. (2018) Analyzing differences among non-adopters of residential stormwater management practices. Landscape and Urban Planning 178, 238-247.

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.

Simon, H.A., Demattè, C., Raffaele Mattioli Foundation. (1997) An empirically based microeconomics. Cambridge University Press, Cambridge, U.K.

Smajgl, A., Morris, S., Heckbert, S. (2009) Water policy impact assessment – combining modelling techniques in the Great Barrier Reef region. Water Policy 11, 191-202.

Steg, L. (2016) Values, Norms, and Intrinsic Motivation to Act Proenvironmentally. Annual Review of Environment and Resources, Vol 41 41, 277-292.

Steg, L., Dreijerink, L., Abrahamse, W. (2005) Factors influencing the acceptability of energy policies: A test of VBN theory. Journal of Environmental Psychology 25, 415-425.

Steg, L., Vlek, C. (2009) Encouraging pro-environmental behaviour: An integrative review and research agenda. Journal of Environmental Psychology 29, 309-317.

Stern, N. (2013) The Structure of Economic Modeling of the Potential Impacts of Climate Change: Grafting Gross Underestimation of Risk onto Already Narrow Science Models. Journal of Economic Literature 51, 838-859.

Stern, N. (2016) Current climate models are grossly misleading. Nature 530, 407-409.

Stern, P.C. (1992) What Psychology Knows About Energy-Conservation. American Psychologist 47, 1224-1232.

Stern, P.C. (2000) Toward a coherent theory of environmentally significant behavior. Journal of Social Issues 56, 407-424.

Stern, P.C., Dietz, T., Abel, T., Guagnano, G.A., Kalof, L. (1999) A value-belief-norm theory of support for social movements. Human Ecology Review 6, 81-97.

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

Stern, P.C., Sovacool, B.K., Dietz, T. (2016b) Towards a science of climate and energy choices. Nature Climate Change 6, 547.

Stern, P.C., Sovacool, B.K., Dietz, T. (2016c) Towards a science of climate and energy choices. Nature Climate Change 6, 547-555.

Tan, C.-S., Ooi, H.-Y., Goh, Y.-N. (2017) A moral extension of the theory of planned behavior to predict consumers' purchase intention for energy-efficient household appliances in Malaysia. Energy Policy 107, 459-471.

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

Tesfatsion, L., (2014) Agent-based computional economics: Growing economies from the bottom up.

Tesfatsion, L., (2018) Chapter 13 - Electric Power Markets in Transition: Agent-Based Modeling Tools for Transactive Energy Support, in: Hommes, C., LeBaron, B. (Eds.), Handbook of Computational Economics. Elsevier, pp. 715-766.

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

Thøgersen, J. (2018) Frugal or green? Basic drivers of energy saving in European households. Journal of Cleaner Production 197, 1521-1530.

Timm, S.N., Deal, B.M. (2017) Understanding the behavioral influences behind Singapore's water management strategies. Journal of Environmental Planning and Management, 1-20.

Tran, M. (2012) Agent-behaviour and network influence on energy innovation diffusion. Communications in Nonlinear Science and Numerical Simulation 17, 3682-3695.

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

van der Werff, E., Steg, L. (2015) One model to predict them all: Predicting energy behaviours with the norm activation model. Energy Research & Social Science 6, 8-14.

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. Annals of Regional Science 57, 335-369.

van Vuuren, D.P., Stehfest, E., Gernaat, D.E.H.J., Doelman, J.C., van den Berg, M., Harmsen, M., de Boer, H.S., Bouwman, L.F., Daioglou, V., Edelenbosch, O.Y., Girod, B., Kram, T., Lassaletta, L., Lucas, P.L., van Meijl, H., Müller, C., van Ruijven, B.J., van der Sluis, S., Tabeau, A. (2017) Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm. Global Environmental Change 42, 237-250.

Vandyck, T., Keramidas, K., Saveyn, B., Kitous, A., Vrontisi, Z. (2016) A global stocktake of the Paris pledges: Implications for energy systems and economy. Global Environmental Change 41, 46-63.

Varian, H.R. (1992) Microeconomic analysis, 3rd ed. Norton, New York.

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

Vassileva, I., Dahlquist, E., Wallin, F., Campillo, J. (2013) Energy consumption feedback devices' impact evaluation on domestic energy use. Applied Energy 106, 314-320.

Verburg, P.H., Dearing, J.A., Dyke, J.G., Leeuw, S.v.d., Seitzinger, S., Steffen, W., Syvitski, J. (2016) Methods and approaches to modelling the Anthropocene. Global Environmental Change 39, 328-340.

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

Wang, Z., Guo, D., Wang, X., Zhang, B., Wang, B. (2018) How does information publicity influence residents' behaviour intentions around e-waste recycling? Resources, Conservation and Recycling 133, 1-9.

Weidlich, A., Veit, D. (2008) A critical survey of agent-based wholesale electricity market models. Energy Economics 30, 1728-1759.

Wilensky, U., (1999) NetLogo.

Wilkerson-Jerde, M.H., Wilensky, U.J. (2015) Patterns, Probabilities, and People: Making Sense of Quantitative Change in Complex Systems. Journal of the Learning Sciences 24, 204-251.

Wilson, C., Dowlatabadi, H. (2007) Models of decision making and residential energy use. Annual Review of Environment and Resources 32, 169-203.

Wilson, C., Pettifor, H., Chryssochoidis, G. (2018) Quantitative modelling of why and how homeowners decide to renovate energy efficiently. Applied energy. 212, 1333-1344.

Wilson, I.A.G., Staffell, I. (2018) Rapid fuel switching from coal to natural gas through effective carbon pricing. Nature Energy 3, 365-372.

Windrum, P., Fagiolo, G., Moneta, A. (2007) Empirical Validation of Agent-Based Models: Alternatives and Prospects. Journal of Artificial Societies and Social Simulation 10.

Yang, Y. (2014) Understanding household switching behavior in the retail electricity market. Energy Policy 69, 406-414.

Zahedi, S., Batista-Foguet, J.M., van Wunnik, L. (2019) Exploring the public's willingness to reduce air pollution and greenhouse gas emissions from private road transport in Catalonia. Science of the Total Environment 646, 850-861.

Zhang, D., Li, J., Su, B. (2017) Social Awareness, Consumer Lifstyle, and Household Carbon Emissions in China. IAEE Energy Forum.

Zhang, Y., Wang, Z., Zhou, G. (2013a) Determinants and implications of employee electricity saving habit: An empirical study in China. Applied Energy 112, 1529-1535.

Zhang, Y.X., Wang, Z.H., Zhou, G.H. (2013b) Antecedents of employee electricity saving behavior in organizations: An empirical study based on norm activation model. Energy Policy 62, 1120-1127.

Summary

Climate change is one of the major global environmental challenges faced by humanity in the 21st century. Global carbon emissions from fossil fuels stand at almost 37 GtCO2 per year and have grown by an average of 2.4% per year so far this century. Based on the latest the global carbon budget report, in 2018 CO2 emissions are still on track to rise by 2.7% (range: 1.8% to 3.7%). Among these, households – directly and indirectly – are responsible for more than 70% of carbon emissions. Hence, decarbonization of the economy requires massive worldwide efforts and a strong involvement of regions, cities, businesses, and individuals in addition to commitments at national levels. While climate mitigation is expanding, UN confirms that we need to urgently and sharply bend the emissions curve by accelerating these efforts to keep the temperature increase to 1.5°C above pre-industrial levels. In the last few years, the discussions about mitigation strategies stress the importance of demand-side solutions and shifts to transdisciplinary and bottom-up approaches in assisting climate mitigation efforts worldwide. The IPCC Special Report on 1.5 degrees names 'behavioural and lifestyle changes' as a vital climate change mitigation strategy complimentary to technological measures. Yet, despite behavioural change being emphasized as a crucial component of mitigation strategies worldwide, empirical studies on individual energy-related choices and behavioural factors impacting them are scarce. Individual energy behaviour, especially when amplified through social context, shapes energy demand and, consequently, carbon emissions. By changing their behaviours, individuals can play an essential role in the transformation process towards a low-carbon society and global emissions reduction. However, explaining and affecting human behaviour is a difficult task since human nature is complex and heterogeneous. As a result, quantitative tools to assess cumulative household emissions, given the

diversity of behaviour and a variety of psychological and social factors influencing it beyond purely economic considerations, are scarce.

This dissertation highlights the potential of behavioural changes among heterogeneous households regarding energy use and their role in mitigating climate change. To do so, (a) a comprehensive household survey is designed and conducted to explore how individuals choose to change their energy behaviour and what factors trigger or inhibit these choices; (b) simulation tools are designed and developed to aggregate these insights and quantitatively assess regional and national impacts of individual choices on carbon emissions; and (c) a novel method to upscale individual energy behaviour for climate change mitigation strategies is presented.

The determinants of the main types of households' energy behaviour: investments in house insulation, installation of solar panels, and energy-efficient appliances; conservation of energy by changing energy-use habits (e.g., switching off unnecessary devices, turning down the heat, and using less energy); and switching between energy suppliers are studied based on the unique data from an extensive survey (N=1,790) from two provinces in EU member states. By employing correlation and probit regression analyses the relationships between individual household attributes (socioeconomic, structural and behavioural factors) and the likelihood of choosing one of the energy actions that contribute to climate change mitigation are quantitatively assessed. The empirical analysis demonstrates that behavioural factors, next to structural factors and education, play at least as important role as do monetary factors, such as income.

An agent-based simulation model is designed and developed to quantify the cumulative impacts of household behavioural changes on regional dynamics of saved energy and CO2 emissions. This model builds up on the advances in agent-based modelling applied in the energy domain, and adds theoretically and empirically-grounded individual behavioural rules that drive households' energy-related choices. The results of this novel model indicate that accounting for the demand-side heterogeneity provides better insights into possible transition pathways to a low-carbon economy and into potential of behavioural changes as a climate change mitigation strategy. In order to facilitate this transition, the broader view on the social environment, cultural practices, public knowledge, producers technologies and services, and the facilities used by consumers are needed to design implementable and politically feasible policy options. Accordingly, the policy mix should also aim at encouraging and facilitating social interactions between individuals/households and promoting and diffusing information that they need. Such accompanying information and value-based policy instruments have the potential to greatly contribute to the effectiveness of conventional price-based and technology-effectiveness policies.

Aggregating behavioural changes of heterogeneous individuals: this dissertation brought attention to the potential of heterogeneous individual energy behavioural changes in terms of the transition to a low-carbon economy at national and EU levels by presenting a novel method for the systematic upscaling of individual heterogeneity and social dynamics (micro-macro models integration). This tool is ideal for studying the dynamic effects of climate change mitigation policy measures targeted at changes in individual energy use practices. The result shows that this transition varies from one region to another. Some regions are lagging behind and others are moving ahead due to heterogeneity in individual sociodemographic (e.g., education and age) and structural characteristics (e.g., type and size of dwellings), behavioural and social traits, and spatial characteristics (e.g., urban vs. rural).

Samenvatting

Klimaatverandering is één van de grootste uitdagingen voor de mensheid in de 21e eeuw. Wereldwijde koolstofemissies van fossiele brandstoffen bedragen bijna 37 $GtCO_2$ per jaar en zijn deze eeuw tot dusver met gemiddeld 2,4% per jaar gegroeid. Uit het laatste wereldwijde koolstofbudgetrapport blijkt dat in 2018 de CO_2-uitstoot nog steeds met 2,7% stijgt (spreidingsbreedte: 1,8% tot 3,7%). Huishoudens dragen met meer dan 70% - direct en indirect - bij aan deze koolstofemissies. Daarom vereist de decarbonisering van de economie naast de verplichtingen op nationaal niveau aanzienlijke wereldwijde inspanningen en een sterke betrokkenheid van regio's, steden, bedrijven en individuen. Terwijl klimaatmitigatie toeneemt, bevestigt de VN dat we de emissiecurve dringend en scherp moeten buigen: inspanningen om de temperatuurstijging binnen 1,5°C te houden ten opzichte van de pre-industriële periode moeten versnelt worden. De afgelopen jaren benadrukken de discussies over mitigatiestrategieën het belang van oplossingen aan de vraagzijde, evenals verschuivingen naar transdisciplinaire en bottom-up benaderingen om de wereldwijde klimaatmitigatie-inspanningen te ondersteunen. Het zogenaamde 1,5-gradenrapport van het Intergouvernementele Panel voor Klimaatverandering (IPCC) noemt 'veranderingen in gedrag en levensstijl' als een essentiële strategie voor mitigatie van klimaatverandering, die complementair is aan technologische maatregelen. Ondanks het feit dat gedragsverandering wordt benadrukt als een cruciaal onderdeel van wereldwijde mitigatiestrategieën zijn empirische studies over individuele energie-gerelateerde keuzes en over de gedragsfactoren die deze keuzes beïnvloeden schaars. Individueel energiegedrag, vooral als het versterkt wordt door de sociale context, bepaalt de energievraag, en, als gevolg, de koolstofemissies. Daarom kunnen individuen door gedragsverandering een essentiële rol spelen in de wereldwijde emissiereductie en in de transformatie naar een koolstofarme samenleving. De complexiteit en heterogeniteit van de menselijke natuur maken het uitleggen en beïnvloeden van menselijk gedrag echter moeilijk. Zodoende, gezien de diversiteit aan gedrag en de verscheidenheid aan psychologische en sociale factoren die gedrag naast puur economische overwegingen beïnvloeden, zijn kwantitatieve hulpmiddelen voor het beoordelen van cumulatieve huishoudelijke emissies schaars.

Dit proefschrift benadrukt het potentieel van gedragsveranderingen bij heterogene huishoudens met betrekking tot energieverbruik en hun rol bij het verzachten van de klimaatverandering. Om dit te doen, is (a) een uitgebreide enquête onder huishoudens uitgezet om te onderzoeken hoe individuen ervoor kiezen hun energiegedrag te veranderen en welke factoren deze keuzes veroorzaken of belemmeren; zijn (b) simulatiehulpmiddelen ontworpen en ontwikkeld om voorgaande inzichten samen te voegen en om de regionale en nationale effecten van individuele keuzes op koolstofemissies kwantitatief te beoordelen; en is (c) een nieuwe methode voorgesteld om individueel energiegedrag op te schalen voor strategieën ter bestrijding van klimaatverandering.

De bepalende factoren voor het energiegedrag van de belangrijkste types huishoudens: investeringen in woningisolatie, installatie van zonnepanelen en energiezuinige apparaten; energiebesparing door verandering van energieverbruiksgewoonten (bijvoorbeeld onnodige apparaten uitschakelen, temperatuur verlagen, en minder energie gebruiken); en de overstap naar andere energieleveranciers worden onderzocht op basis van de unieke gegevens van een omvangrijke enquête (N = 1.790) uit twee provincies in EU-lidstaten.

Door correlatie- en probit-regressieanalyses toe te passen worden de relaties tussen individuele kenmerken van huishoudens (socio-economische, structurele en factoren m.b.t. gedrag) en de waarschijnlijkheid om één van de acties te kiezen die energieverbruik verlagen en bijdragen aan klimaatmitigatie kwantitatief beoordeeld. De empirische analyse laat zien dat gedragsfactoren, naast structurele factoren en opleiding, minstens een even belangrijke rol spelen als monetaire factoren, zoals inkomen.

Een agent-based simulatiemodel is ontworpen en ontwikkeld om de cumulatieve effecten van gedragsveranderingen van huishoudens op de regionale dynamieken van besparing van energie en CO_2-emissies te kwantificeren. Dit model bouwt voort op agent-based modellen die in het energiedomein worden toegepast, en voegt op basis van theoretische en empirische inzichten individuele gedragsregels toe die de energie-gerelateerde keuzes van huishoudens beïnvloeden. De resultaten van dit innovatieve model tonen aan dat rekening houden met de heterogeniteit aan de vraagzijde betere inzichten biedt in mogelijke transitiepaden naar een koolstofarme economie en in het potentieel van gedragsveranderingen als klimaatmitigatiestrategie. Om deze transitie door het ontwerp van uitvoerbare en politiek-haalbare beleidsopties te faciliteren is een bredere visie nodig op de sociale omgeving, culturele gewoontes, algemene kennis, technologieën en diensten van producenten en de faciliteiten die consumenten gebruiken. Bijgevolg moet de beleidsmix ook gericht zijn op het stimuleren en faciliteren van sociale interacties tussen individuen/huishoudens en het bevorderen en verspreiden van informatie die zij nodig hebben. Dergelijke begeleidende informatie en op waarden gebaseerde beleidsinstrumenten kunnen aanzienlijk bijdragen aan de effectiviteit van conventionele beleidsmaatregelen op het gebied van prijs en technologie-effectiviteit.

Gedragsveranderingen van heterogene individuen aggregeren: dit proefschrift vestigt de aandacht op het potentieel van heterogene individuele gedragsveranderingen met betrekking tot energie voor de transitie naar een koolstofarme economie op nationaal en EU-niveau door een nieuwe methode voor de systematische opschaling van individuele heterogeniteit en sociale dynamieken voor te stellen (integratie van micro-macro modellen). Deze tool is ideaal voor het bestuderen van de dynamische effecten van beleidsmaatregelen voor klimaatmitigatie gericht op veranderingen in individuele energieverbruiksgewoontes. Het resultaat laat zien dat de transitie van regio tot regio verschilt. Sommige regio's blijven achter en anderen lopen op kop vanwege de heterogeniteit in individuele socio-demografische factoren (bijv. opleidingsniveau en leeftijd), structurele kenmerken (bijv. het type en de grootte van woningen), gedrags- en sociale kenmerken en ruimtelijke kenmerken (bijv. stedelijk vs. landelijk).

Biosketch

Leila Niamir was born in Tehran, Iran, in 1988. She graduated summa cum laude from her MSc. degree from University of Tehran in Management and Information Science, 2012. She developed her skills on web based information systems and developing online databases during her MSc thesis research. In 2013, Leila received a full Erasmus Mundus scholarship for Post-graduate program in Geo-informatics, Faculty of Geo-information Science and Earth Observation, University of Twente. As the final project, she designed and implemented a pilot real-time pollution monitoring system. In the year 2014, she joined Department of Governance and Technology for Sustainability, University of Twente as a researcher and PhD student. Leila's PhD was part of the COMPLEX EU FP7 project, where she actively collaborated with an international team of 17 academic partners. In 2016, she got a scholarship to visit Sorbonne University, France and to participate in SMART Labex summer school which brought her further insight into computational social and behavioural sciences. In the same year, Leila started her collaboration with PBL Netherlands Environmental Assessment Agency as a visiting researcher. There she followed her research on mirco-macro models integration. In 2017, she was selected as a young scientist to visit Internarial Institute of Applied System Analysis (IIASA), Austria for three months. This visit was funded by a grant that she received from The Netherlands Organisation for Scientific Research (NWO). In 2018, she received a scholarship from Global Environments Academy to join their summer program and visit Oxford Environmental Change Institute, UK. As the next step she plans to pursue her career in science-policy interface on climate change mitigation and energy.

Scientific contribution

Peer reviewed papers

- Niamir, L., Filatova, T., Voinov, A., Bressers, H. (2018) Transition to low-carbon economy: Assessing cumulative impacts of individual behavioral changes. Energy Policy 118, 325-345.
- Niamir, L., Ivanova, O., Filatova, T., Voinov, A. (2018) Tracing Macroeconomic Impacts of Individual Behavioral Changes through Model Integration. IFAC-PapersOnLine 51, 96-101.
- Niamir, L., Ivanova, O., Filatova, T., Voinov, A., Bressers, H. (2018) Demand-side solutions for climate change mitigation: bottom-up drivers of household energy behaviour change. Applied Energy (under review)
- Niamir, L., Kiesewetter, G., Wagner, F., Schöpp, W., Filatova, T., Voinov, A., Bressers, H. (2018c) Assessing the macroeconomic impacts of individuals energy-efficient behavior on upstream carbon emissions. Climatic Change (under review).
- Niamir, L., Ivanova, O., Filatova, T., (2018) Economy-wide impacts of climate change mitigation behaviour among heterogeneous agents: linking agent-based and computable general equilibrium models. Global Environmental Change (under review).
- Belete, G., Voinov, A., Bulavskaya, T., Niamir, L., Dhavala, K., Arto, I., Moghayer, S., Filatova, T. (2018) Web service based approach to linking heterogeneous climate-energy-economy models for climate change mitigation analysis. Applied Energy (under review).
- Niamir, L., Filatova, T., Voinov, A., Bressers, H. (2018). Impact of households' behavioural change on the energy demand in a transition to low-carbon economy. Procceding of IAEE International Conference, Groningen-The Netherlands.

- Niamir, L., Filatova, T., (2016) From Climate Change Awareness to Energy Efficient Behaviour, Procceding of 8th International Congress on Environmental Modelling and Software, Toulouse, France.
- Niamir, L., Filatova, T., (2015) Linking Agent-based energy market with Computable General Equilibrium Model: an Integrated Approach to Climate-Economy-Energy System, Procceding of 20th WEHIA Conference, Sophia Antipolis, France.

Reports

- Inaki, A., Boonman, H., Bulavskaya, T., Dhavala, K., Filatova, T., Hu, J., Moghayer, S.M., Niamir, L., (2016) Modelling system documentation and Final Report on results and policy Briefing. EU FP7 COMPLEX. Report D5.6 and D5.7, August 2016: 63 p.
- Moghayer, S.M., Arto, I., Dhavala, K., Filatova, T., Niamir, L., Voinov, A., (2015) Report on COMPLEX CEE System Models Database. EU FP7 COMPLEX. Report D5.5, December 2015.
- Kovalevsky, D.V., Arto, I., Dhavala, K., Filatova, T., Hasselmann, K., Moghayer, S.M., Niamir, L., Voinov, A., (2015) Integration of climate scenaria in the Modelling system. EU FP7 COMPLEX. Report D5.4, November 2015: 24 p.
- Filatova, T., Moghayer, S.M., Arto, I., Belete, G., Dhavala, K., Hasselmann, K., Ivanova, O., Kovalevsky, D.V Niamir, L., Voinov, A., (2014). Dynamics of climate-energy-economy systems: development of a methodological framework for an integrated system of models. EU FP7 COMPLEX. Report D5.3, December: 37 p.

Book chapters

- Filatova, T., Niamir, L., (2018) Changing climate – changing behaviour: empirical agent based computational models for climate change economics, in: Lamperti, F., Monasterolo, I., Roventini, A. (Eds.),

Complexity and Climate Change: An Evolutionary Political Economy Approach. Taylor & Francis.

- 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.
- Niamir, L., Filatova, T., (2016). Tracing Behavioural Change in Climate-Economy-Energy Systems: Agent-Based Energy Market and Computable General Equilibrium Model. Advancing in Modelling and Integrated Assessment, COMPLEX, Vol.4.
- Niamir, L., Filatova, T., (2016). Nonlinearities in retail electricity markets: modelling residential energy demand in the Navarre Region, Spain. Advancing in Modelling and Integrated Assessment, COMPLEX, Vol.4.

Selected talks and presentations

- Global Environments Academy 2018, 25 July- 11 August, Oxford-UK.
- IAEE International Conference 2018, 10-13 June, Groningen-Netherlands.
- IFAC Workshop on Integrated Assessment Modelling for Environmental Systems 2018, 10-11 May, Brescia-Italy.
- International Conference of Impacts World 2017, 11-13 October, Potsdam-Germany.*
- Conference on Complex Systems 2017, 17-22 September, Cancun-Mexico.
- International Institute for Applied Systems Analysis (IIASA) 2017, 24-25 August, Vienna-Austria.

* Best Poster Award

- SMART School on Computational Social and Behavioural Sciences 2016, 5-7 September, Paris-France.
- International Congress on Environmental Modelling and Software 2016, 10-14 July, Toulouse-France.
- International Institute for Applied Systems Analysis (IIASA) 2016, 15 June, Vienna-Austria.
- Annual Workshop on the Economic Science with Heterogeneous Interacting Agents 2015, 21-23 May, Sophia Antipolis-France.
- Social Simulation Conference 2015, 14-18 September, Groningen-The Netherlands.