International Congress on Environmental Modelling and Software

8th International Congress on Environmental Modelling and Software - Toulouse, France - July 2016

Jul 13th, 8:50 AM - 9:10 AM

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International Environmental Modelling and Software Society (iEMSs)
8th International Congress on Environmental Modelling and Software
Toulouse, France, Sabine Sauvage, José-Miguel Sánchez-Pérez, Andrea Rizzoli (Eds.)
http://www.iemss.org/society/index.php/iemss-2016-proceedings

From Climate Change Awareness to Energy Efficient Behaviour

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Abstract: Understanding and predicting how climate will change, and whether and how a transition to low-carbon economies will develop over the next century is of vital importance. Nowadays there is high competition between countries to achieve a low-carbon economy. They are examining different ways e.g. different energy efficient technologies and low-carbon energy sources, however they believe that human choices and behavioural change has a crucial impact, which is many times discussed in the literature as well. In this paper, we aim to discuss challenges related to modelling behavioural changes on the demand side and show effect of the demand side activation (households behavioural change) in decreasing regional energy use and emissions. In following we will discuss (a) the challenges of studying households energy choices in the context of transition to low-carbon economy, and (b) the importance of a thorough underpinnings of modelling choices using inputs of behavioural sciences on climate and environment knowledge and awareness in households decisions. We further present an agent-based model rooted in established psychology theories of behavioural change and supported by empirical survey data.

Keywords: Low-carbon Economy; Energy Transition; Agent-based Modelling; Renewable Energy; Knowledge activation; Norm Activation Theory

1 Introduction

Observing extreme weather events such as floods, droughts or wild forest fires demonstrate how much climate can affect lives of individuals, communities, cities, regions and the entire economy. Understanding and predicting how climate will change, and whether and how a transition to low-carbon economies will develop over the next century is of vital importance. Worldwide countries agree to set up major milestones in an effort to combat climate change. The 21st Conference of the Parties (COP21) held in Paris in December 2015 was successful in making steps towards a new global agreement to limit greenhouse-gas emission. Governments are determined to act to the full extent necessary to achieve the goals and to revise their national energy agendas to keep the rise in global average temperatures below 1.5 degrees Celsius. European Union in particular is pioneering in this domain by exploring the options for cost-efficient ways to make the European economy more climate-friendly and less energy-consuming already for decades (EEA 2013; ESRB 2016; EU 2011; Faber, et al. 2012).

There are several ways to achieve a transition to low-carbon economy: technological energy efficiency solutions, switching to low-carbon energy sources, as well as behavioural change (McKinsey 2009). Yet, while the impacts of the former two are relatively feasible to trace with the help of numerous macroeconomic, integrated assessment and technological models, quantifying the macro impacts of energy-related behavioural changes is a challenge. It is also essential to consider any feedbacks between diffusion of energy efficient technologies or low-carbon energy sources and behavioural response to avoid any unforeseen and undesirable consequences, e.g. rebound effect. Therefore, it is worth to consider the whole energy (retail) market to get a comprehensive view of demand (households) and supply (energy providers) sides and their relation and interactions. The supply side of the energy market is widely studied, and they resemble more rational optimizer agents. However the household energy consumption is as important as transport and industry (OECD and IEA 2015). Here we are talking about human choices and behavioural change, importance of which is widely discussed in the literature (Frederiks, et al. 2015) and is acknowledged in the EU reports (EEA 2013; EU 2011; OECD and IEA 2015). Human behavioural change significantly influences energy use in the residential sector. Although many researchers discuss the potential on the demand side to stimulate a transition to low-carbon economy, it seems to be quite challenging to really activate this potential in practice. Demand side activation is one of the hot topics on the EU research agenda. In the following we will discuss importance of human awareness and its consequences on their behavioural change through transition to low-carbon economy using agent-based modelling method and established psychology and sociology theories.

2 Role of households in a transition to low-carbon economy

Residential energy demand accounts for almost 24% of GHG emissions in Europe. Changing energy habits and choices households make is usually labelled as behavioural change. Some rough assessments indicate that behavioural change alone can contribute from 4% of overall CO2 emissions (McKinsey 2009) and much higher according to other studies (Faber, et al. 2012). Thus, activating demand side to take part in the transition to low carbon economy is essential. The question is how to quantify and make a proper assessment of households behavioural changes on the overall energy and emission reduction.

In traditional economic theories, human decision making and behaviour are based on a rational choice (Becker 1962; Simon 1955; Simon 1957). Neoclassical economics models also assume rational choice theory (Coleman 1992; Henry 2011; Roy Weintraub 1993) and that people have stable preferences, perfect information and make rational choices. Based on these assumptions, economic models present people who make decisions just based on preferences and budget constraints, therefore their behavioural change can be stimulated either with more information (e.g. increasing knowledge) or giving them more options to choose (Frederiks, et al. 2015). However, many empirical studies in psychology and behavioural economics show that consumer choices and actions often deviate from these assumptions of the rationality, and there are certain persistence biases in human decision making, which lead them to have different behaviour (Frederiks, et al. 2015; Kahneman 2003; Pollitt and Shaorshadze 2013; Stern 1992; Wilson and Dowlatabadi 2007).

Therefore, in order to trace aggregated impacts of households behavioural changes and their potential contribution to a transition to low-carbon energy, we seek to combine agent-based modelling and empirical studies. In order to investigate a behavioural change, human decision making in a specific context should be studied. Agent-based modelling gives us a unique opportunity to model the decision-making of heterogeneous agents (households) that are bounded rational and engage in interactions. However, this requires careful and detailed model design, implementation and validation. The agent-based model NIROO is designed to simulate heterogeneous households which are different in socio-demographic factors such as income, saving, education level, and age. These households make their energy decisions based on psychology factors (e.g. awareness, personal norms, social norms) and their socio-demographic characteristics (e.g. income, saving). We categorized their decisions in 3 main groups: energy-related investments, energy conservation choices, and switching to a low carbon energy source. The 3 groups of actions can be further specified to be operationalized in the model. For instance, energy-related investment may include investments in new technologies (e.g. installing solar panel), installing efficient appliances (e.g. A++ washing machine), or house insulation (e.g. double or triple glazing). To shed light on how the decision-making process takes place we designed a series of surveys based on psychology, sociology and social network theories (section 3) and we use this information to specify behavioural rules of agents as well as to parameterize the simulation model. In this paper we just focus on the effect of climate change and environment awareness on the regional energy use, as awareness is one of the important drivers of households behavioural change.

3 Empirical studies

Many of the demand-side behavioral energy models use of the three behavioral theories rooted in psychology and sociology. Namely: Theory of Planned Behavior (TPB), Protection Motivation Theory (PMT), and Norm Activation Theory (NAT). TPB which is formulated by Ajzan and Fishbein in 1980 based on the Theory Reasoned Action. It is one of the most influential theories in social and health psychology (Armitage and Conner 2001) and was used in many pro-environmental studies (Onwezen et al., 2013). TPB assumes that an intention (to act) is determined by 3 main things: human attitude toward specific behavior (action), subjective norm, and perceived behavioral control. PMT was introduced by Rogers in 1975 and it provides a valuable framework to explain pro-environmental choices, by employing a wide set of predictors (Bockarjova and Steg 2014). This theory mostly is used in risk adaptive behavior models, and it would be a good choice in study climate change adaptation. Therefore PMT is not the best choices for our study. However, NAT, which is originally developed by Schwartz (1977), operates in context of altruistic and environmentally friendly behavioral. It is mostly focused on anticipating pride and on studying an evolution of guilt feelings.

Knowledge and awareness of households about their environment and climate change, their self-efficacy, and environmentally-friendly behavior are important drivers of choice as demonstrated by psychology and environmental studies (Bamberg, et al. 2007; Bamberg and Moser 2007; Onwezen, et al. 2013). However, they are not an inherit part of TPB. Therefore we designed integrated TPB and NAT framework, which forms the core behind a large-scale survey model and which supports our simulation model. Our survey model assumes of 3 main steps to reach to the particular action: knowledge activation, motivation, consideration and evaluation. In each step, several psychological factors (e.g. awareness, personal norms, feeling guilt, subjective norms) and socio-demographic drivers and barriers (e.g. household income, saving, energy consumption, dwelling characteristics) are considered and calculated based on TPB and NAT theories. However, in order to get a clear view and find out to what extent knowledge and awareness of households (γ) impacts households behavioral change, we are going to just focus on knowledge activation of households in the process of decision making. The knowledge activation measurement is the main part of NAT theory.

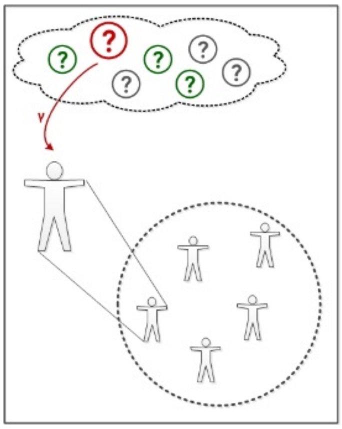

Figure 1: Households behavioral change drivers and barriers

The questions in the knowledge activation part of the survey are designed to elicit: (a) a respondent's knowledge about environment, climate change, and energy sources, and (b) how much a person is aware of environmental and climate change issues, and (c) how much he/she believes that his/her energy decisions contribute to environmental issues and specifically to climate change. Knowledge activation is measured in comparable ways with Likert scales: 1= "Not at all serious" and 7= "Extremely serious" , 1= "Strongly disagree" and 7= "Strongly agree", 1= "Definitely not true" and 7= "Definitely true". There is some overlap between questions: the environmental and climate change knowledge is measured with 8 items (e.g. climate change is caused by a hole in the earth's atmosphere), Climate change, Economy and Environmental issues (CEE) awareness is measured with 11 items (e.g. how serious are the environmental issues facing the world: air pollution, climate change,…), and Energy Decisions (ED) awareness with 6 items (e.g. I am feeling good when I am using eco-friendly products).

The entire survey has been tested during the COMPLEX stakeholder meeting/workshop[1], Sigtuna-Sweden, January 2016. After the successful pilot run, we are currently running this survey in NUTS2 regions in two EU case studies. The case studies were chosen based on a range of criteria: different climate zones, difference in culture and GDP which itself brought different technology diffusion (e.g. solar panel, wind turbine, biomass).

[1] http://owsgip.itc.utwente.nl/projects/complex/index.php/2-uncategorised/10-complex-project-events

Table 1: Knowledge activation and intention measures

Awareness	Average
1.Environmental and climate change Knowledge	Knowledge = 5.70
2.**C**limate change, **E**conomy and **E**nvironmental issues awareness	CEE Awareness = 5.45
3.**E**nergy **D**ecisions awareness	ED Awareness = 5.74
Intention	
1.Investment intention (intention 1)	Intention 1 = 0.6
2.Energy conservation intention (intention 2)	Intention 2 = 0.86
3.Switching intention (intention 3)	Intention 3 = 0.46

*All items were measured with Likert scales (1-7) and the sample size is 16 households

Figure 2 illustrated the households knowledge activation parameters and their standard deviation based on the pilot survey. For instance, both respondents number 5 and 12 have the lowest standard deviation among these three factors: knowledge, CEE awareness and ED awareness, although number 5 has more awareness in general and in particular has more environmental and climate change knowledge. Also both respondents number 8 and 14 have the highest standard deviation, however they have very different thoughts on energy decision awareness. In addition, with these 3 small figures at the left you can track each households knowledge activation parameters: knowledge, CEE awareness, and ED awareness.

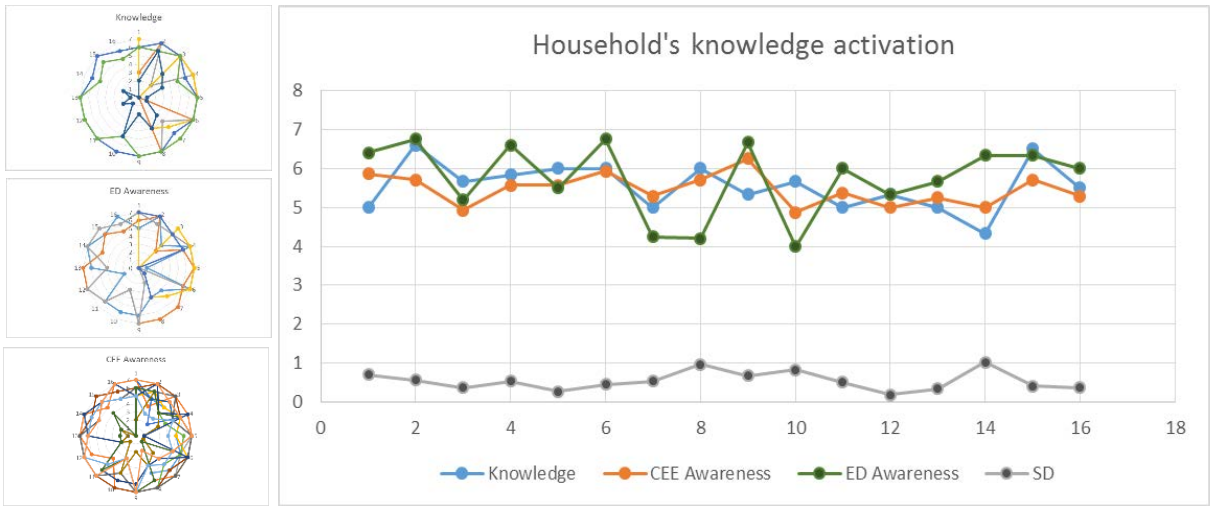

Figure 2: Houshold's knowledge activation

4 Model structure and parameterization

The agent-based energy market model is designed and implemented to study Nonlinearities in Residential lOw-carbOn economy transition (NIROO). NIROO specifically focuses on households' energy use and potential behavioural change and aims to study demand-side activation and potential non-marginal changes in energy markets. NIROO disaggregates the residential energy (electricity and heating) demand side to trace cumulative impacts of behavioral change among heterogeneous households over time and space. Although in the model we consider the supply side endogenously with integrating this model and CGE model, to reach to the market clearing procedure in order to get better view of households behavioral change in whole energy market (Niamir and Filatova 2015a). The current model is coded in NetLogo 5.2 with GIS extensions. We used open source applications, such as PostgreSQL and R, for the spatio-temporal and statistical analyses.

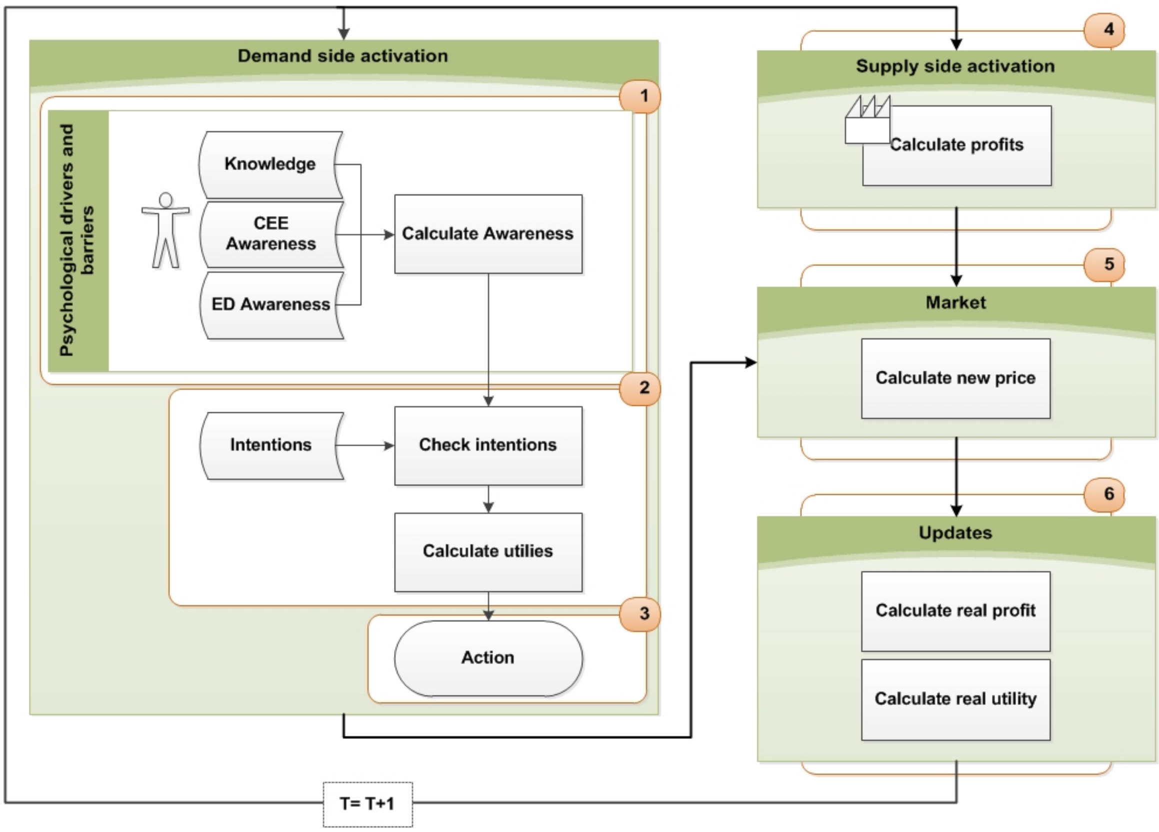

Figure 3: Model time step

The model consists of heterogeneous households with different preferences, awareness of climate change, and socio-economic characteristics, which lead to various energy consumption choices. As it is illustrated in Figure 3, firstly households have awareness about the state of climate and environmental preferences (γ), which could potentially be heterogeneous and change over time. This awareness (γ) is calculated and normalized based on the input from the survey – mainly based on psychological factors – which are described in the section 3. Secondly, households utilities that they expect to receive (U) are calculated based on given energy prices – low-carbon sources (LCE) and fossil fuels sources (FF)- and under budget constraints. Households receive utility from consuming energy (E) and a composite good (Z) between which its budget is shared (α) (equation 1).

$$U = Z^{\alpha} * E^{(1-\alpha)} * C^{\gamma} \quad (1)$$

$$\gamma = \text{Knowledge} + \text{CEE awareness} + \text{ED awareness} \quad (2)$$

Thirdly, households make their energy decision based on their utilities (U_{lce} and U_{ff}), the current energy source statues (LCE user/ FF user), and also their intentions to undertake any of the 3 main actions. The intentions are measured through the survey based on psychological factors (section 3). Eventually we would like to consider the following actions (as coded in the survey): Green investment, Green energy conservation, switching to a greener provider (more share of LCE), Grey investment, Grey energy conservation and switching to LCE provider.

Fourthly, currently the supply side is presented by heterogeneous energy providers, which may deliver either electricity based on LCE or FF. Within the COMPLEX EU FP7 project our model is being integrated with a Computable General Equilibrium model (CGE) which is designed and implemented at TNO, the Netherlands (Filatova, et al. 2014). Thus, at this stage we do not go into the details of modelling the various energy providers as this information will come from CGE. Instead, we simulate simplified providers with different shares of LCE and FF electricity production. In retail electricity market, profits are calculated regarding to prices (P_{lce}/P_{ff}), and share of LCE vs. FF, to deliver next time step in order to optimize their profits (equation 3).

$$\text{Profit} = \text{Total Revenue} - \text{Total Cost} \tag{3}$$

Profit is calculated based on total revenue and total cost. We considered cumulative price growth (CPG), market price of electricity (P), and electricity production (Q) to estimate the total revenue of provider (equation 4).

$$\text{Profit} = (CPG * P * Q) - COST \tag{4}$$

Fifthly, new energy prices (P^*_{lce}/P^*_{ff}) and market shares of LCE and FF electricity are an emergent outcome of our model. Yet, a household needs to form price expectations regarding energy prices to be able to take any of the 3 groups of energy-related decisions. We chose “gradual price adjustment” approach for price determination for our model (Niamir and Filatova 2015b). The price is often changed as a fixed proportion (α) of the excess demand as in equation 5 (LeBaron 2006).

$$P_{t+1} = P_t + \alpha\,(D\,(P_t) - S\,(P_t)) \tag{5}$$

In our last paper Niamir and Filatova (2015b), we discussed four market clearing approaches. Although “gradual price adjustment” approach could have many similarities with other approaches, namely with the discrete-time version of the standard Walrasian price adjustment mechanism. There are also some differences. This approach same as in the Walrasian price adjustment mechanism, all agents in the market are price taker and utility maximizer (Kumar and Shubik 2004). While we do not have individual optimization to compute the optimal desired quantities of commodities. In our approach households satisfied by maximizing their utility expectation based on previous period price. Moreover, due to no optimization on the individual level, there might be no stability in this market as well, because our households behavioral change and decisions modelled based on the cognitive process which motivated by psychological theories.

Lastly, at the last stage utilities of households and profits of providers are updated based on the new prices (P^*_{lce}/P^*_{ff}). Then we will go to the next time step.

5 Preliminary results and discussion

We present a work in progress with modified NIROO model based on our second pilot study, COMPLEX stakeholder workshop, Sigtuna, Sweden. Here we try to show our primary observations and results. At the conference we plan to present the final simulation results of the NIROO model and discuss the trends in awareness, actions, and decisions satisfactory.

(a)

(b)

Figure 4: (a) Households actions map. (b) orange indicates investments, purple is LCE user conserving energy, pink FF user conserving energy, grey FF user switching to green, and green LCE user swithcing to greener.

NIROO model is integrated with CGE model within our first NUT2 case study, Navarre region-Spain and based on income quantiles (Niamir and Filatova 2015b). Later, the knowledge activation data from our pilot survey is fed to the NIROO model based on 5 income groups. Therefore, households make their energy decisions based on their utility expectations, awareness, and intentions. The primary results indicate that when households' awareness is increased, they have more intention to change their behavior and take actions, except when they find the financial problem. Figure 4 is a snapshot of a simulation that represents spatial distribution of various actions.

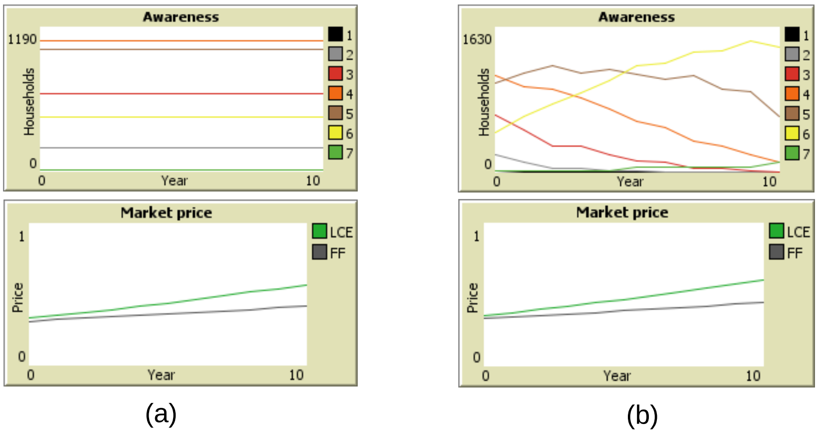

Figure 5: Effect of household's awareness on energy market prices (LCE and FF energy), (a) Households have stable awareness (b) Households have learned each year through social network, so the awareness is increased.

Figure 5 shows the impact of individuals on energy market prices, with and without learning algorithms. Moreover, section 3 mentions that households tend more to pursue energy conservation (intention 2 = 0.86). Here figure 5 shows that the standard deviation of energy conservation is less than 2 others. So we can conclude that there is a correlation between more intention and less action dispersion.

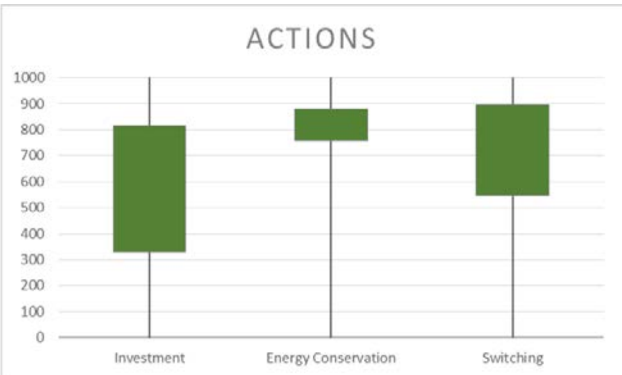

Figure 6: Variability of actions

The future work will go on in two directions. Firstly, we are going to analysis the full scale survey data and calibrate the model based on the outcome of our survey. Then we also aim to investigate the effect of social networks on increasing environmental and climate change awareness, and on the same path on residential low-carbon transition. Secondly, we aim to develop NIROO further and check sensitivity and robustness of outcomes of the ABM parameterized with the survey-data.

ACKNOWLEDGMENTS

Funding from the EU FP7 COMPLEX project 308601 is greatly acknowledged.

REFERENCES

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

Bamberg, S., M. Hunecke, and A. Blobaum, 2007. Social context, personal norms and the use of public transportation: Two field studies. Journal of Environmental Psychology 27(3):190-203.

Bamberg, S., and G. Moser, 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(1):14-25.

Becker, G. S., 1962. Irrational Behavior and Economic-Theory. Journal of Political Economy 70(1):1-13.

Bockarjova, M., and L. Steg, 2014. Can Protection Motivation Theory predict pro-environmental behavior? Explaining the adoption of electric vehicles in the Netherlands. Global Environmental Change-Human and Policy Dimensions 28:276-288.

Coleman, J. S., 1992. Some Points on Choice in Education. Sociology of Education 65(4):260-262.

EEA, 2013. Achieving energy efficiency through behaviour change: what does it take?

ESRB, 2016. Too late, too sudden: Transition to a low-carbon economy and systemic risk.

EU, 2011.Communication from the commission to the European parliament, the council, the European economic and social committee and the committee of the region. Energy Efficiency Plan: EU.

Faber, J., et al., 2012. Behavioural Climate Change Mitigation Options and Their Appropriate Inclusion in Quantitative Longer Term Policy Scenarios.

Filatova, T., et al. , 2014. Dynamics of climate-energy-economy systems: development of a methodological framework for an integrated system of models.

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

Henry, John F., 2011. The making of neoclassical economics. Boston: Unwin Hyman.

Kahneman, D., 2003. A psychological perspective on economics. American Economic Review 93(2):162-168.

Kumar, A., and M. Shubik, 2004. Variations on Theme of Scarf's Counter-Example. Computational Economics 24:1-19.

LeBaron, B., 2006. Agent-based computational finance In Handbook of Computational Economics. L. Tesfatsion and K.L. Judd, eds. Amsterdam, The Netherlands: North-Holland.

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

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

Niamir, L., and T. Filatova, 2015b. Transition to Low-carbon Economy: Simulating Nonlinearities in the Electricity Market, Navarre Region-Spain. 11th Social Simulation Conference (SSC2015), Groningen, The Netherlands, 2015b. Springer Proceedings in Complexity.

OECD, and IEA, 2015. Energy and Climate change.

Onwezen, M. C., G. Antonides, and J. Bartels, 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.

Pollitt, M.G., and I. Shaorshadze, 2013.The role of behavioural economics in energy and climate policy. In Handbook on Energy and Climate Change: Edward Elgar.

Roy Weintraub, E., 1993. Neoclassical Economics. In The Concise Encyclopedia of Economics: Library of Economics and Liberty.

Schwartz, Shalom H., 1977. Normative Influences on Altruism1. In Advances in Experimental Social Psychology. B. Leonard, ed. Pp. 221-279: Academic Press.

Simon, H. A., 1955. A Behavioral Model of Rational Choice. The Quarterly Journal of Economics 69(1):99-118.

Simon, Herbert A., 1957. Models of man: social and rational; mathematical essays on rational human behavior in a social setting. New York,: Wiley.

Stern, P. C., 1992. What Psychology Knows About Energy-Conservation. American Psychologist 47(10):1224-1232.

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