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IFAC PapersOnLine 51-5 (2018) 96–101

Tracing Macroeconomic Impacts of Individual Behavioral Changes through Model Integration

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Abstract: The discourse on climate change stresses the importance of individual behavioral changes and shifts in social norms to assist both climate mitigation efforts worldwide. A design of an effective and efficient climate policy calls for decision support tools that are able to quantify cumulative impacts of individual behaviour and can integrate bottom-up processes into the traditional decision support tools. We propose an integrated system of models that combines strengths of macro and micro approaches to trace the cross-scale feedbacks in socio-economic processes in residential energy markets at provincial and national scales. This paper explores the feasibility of such hybrid models to study dynamic effects of climate change mitigation policy measures targeted at changes in residential energy use practices. We present an example of an agent-based energy model (BENCH) integrated with a EU-EMS computable general equilibrium model. We discusses methodological advancements and open challenges with respect to the integrated system of models.

Keywords: Agent-based Model, Computable General Equilibrium Model, Energy Economics, Behavioural change, Discrete Choice Model, Structural Equation Model**,** Latent Analysis, Low-carbon Economy Transition, Climate Change Mitigation, Integrated Assessment Models, Microeconomic Choices, Energy Efficiency

1. INTRODUCTION

Coupled climate-economy systems are complex adaptive systems. Strong feedbacks between climate and economy are realized through energy: economy needs energy for development in any sector. Simultaneously, emissions need to stabilize and even become negative to avoid catastrophic climate change (IPCC, 2014). To be able to formulate an appropriate energy policy for this complex adaptive system, policymakers should ideally have decision support tools that are able to quantitatively assess cumulative impacts of behavioral changes among many heterogeneous households on energy markets and overall economy over the coming decades. 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). Yet, behavioral shifts among households are often modeled in a rudimentary way assuming a representative consumer (a group), a perfectly informed choice based on rational optimization, and instantly equilibrating markets. Going beyond a stylized representation of a perfectly informed optimizer requires a theoretically and empirically solid alternative (Niamir et al., 2018). An Integrated System of Models (ISM) can be used to address policy questions and methodological challenges when assessing CEE dynamics in the presence of nonlinearities, if designed coherently (Voinov and Shugart, 2013). This may be especially relevant when feedbacks between processes occurring at different scales are to be considered.

Computable General Equilibrium (CGE) models are predominately used to support climate change policy debates, particularly in the economics of climate change mitigation (Babatunde et al., 2017). CGE models are strong in tracing cross-sectoral impacts and linking to readily-available datasets. However, several challenges underline the standard macroeconomics and CGE models. They use assumptions such as rational and representative agents with prefect information and complete markets and aggregated production functions. These deficiencies are acute enough in simulation measures (Babatunde et al., 2017), and could potentially lead to wrong policy response (Stern, 2016).

Agent Based Modeling (ABM) is a bottom-up approach that may extend traditional microeconomics models by bringing heterogeneity among agents, by making them adaptive in dynamic settings, and by accommodating bounded rationality

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10.1016/j.ifacol.2018.06.217

and imperfect information. Yet, they are limited due to a gap between the detailed knowledge on agents' behavior and difficulties with generalization and scaling up of their results (Humphreys and Imbert, 2012). Therefore, ABM CGE models may have synergies when combined. Linking ABMs and dynamic CGE models may cover the trade-offs between complexity and realism (Babatunde et al., 2017). CGE models can simulate the connections across all sectors of the economy in a transparent way, while ABMs zoom into a specific sector such as energy where uncertainty and heterogeneity are known to be significant (Niamir and Filatova, 2015). Yet, there are a number of methodological dissonances that need to be resolved.

This research aims at exploring the feasibility of coupling models –macro with micro– to study climate change mitigation policy measures that target behavioral changes and are relevant at provincial and national levels. In particular, we present an example of an agent-based energy (BENCH) model integrated with a CGE EU-EMS model. In addition, to assuring data transfer, we present the design of a theoretically coherent ISM framework that marries two methodologically alien approaches.

2. AGENT-BASED MODEL (BENCH)

2.1 BENCH Agent-based model

The BENCH agent-based model[1] is designed to investigate the process of individuals (households) energy-efficient decision-making, and to study the cumulative impacts of behavioral changes among heterogeneous households over time and space. In the current model, there are three representative electricity producer agents (Grey, Green and Super Green) and household agents, which are geographically spread over the territory of a provincial (NUTS2) level. The model is applied to two EU province and is parameterized using household survey data: in the Navarre province in Spain (N=800 respondents) and Overijssel province in the Netherlands (N=1400 respondents). The model is coded in NetLogo 6.0.1 with GIS extension (Wilensky, 1999). We used open source applications, such as QGIS and R, for the spatio-temporal and statistical analyses. To make agent-based modeling useful we must proceed systemically, avoiding arbitrary assumptions, carefully grounding and testing each piece of the model against reality (Farmer and Foley, 2009). Therefore, we designed and implemented the BENCH model grounded in psychological theories, by gradually relaxing standard economic assumptions and calibrating them with the empirical survey data.

2.2 BENCH conceptual model

The BENCH model disaggregates residential demand and focuses on representing behavioral changes regarding energy use among households. We assume that households' decisions are driven by (a) behavioral activation and (b) economic activation. In the behavioral part, the psychological and social aspects of a households' energy-efficient choices play a role. When behavioral factors are considered and an individual intention to act is high, households proceed with assessing economic factors. Here households estimate their utilities of taking one of three actions: investment, conservation and switching. These are compared to utility of inaction to choose the highest (Figure 1).

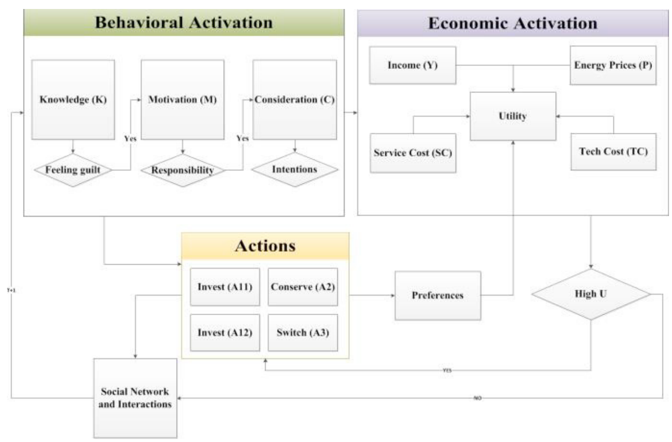

Fig. 1. BENCH agent-based model conceptual model

2.2.1 Behavioural activation

Based on different internal and external barriers and drivers, households may have different knowledge and awareness levels about the state of the climate and environmental issues, motivation levels to change their energy related behavior, and consideration levels when they perform costs and utility assessments. All households' 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 a Likert scale, in the range of 1-7 as in the survey. While 1 stands for the lowest, 7 is the highest level.

At initialization, households' *knowledge and awareness (K)* is calculated and normalized based on the input from the survey by combining climate-energy-environment knowledge (CEEK), climate-energy-environment awareness (CEEA), and energy-related decision awareness (EDA) values, each measured on a 7 score Likert scale (Eq.1). 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)*.

$$K = \frac{AVG\ (CEEK\ + CEEA\ + EDA\ )}{7} \qquad (1)$$

[1] **B**ehavioral change in **EN**ergy **C**onsumption of **H**ouseholds (*BENCH*) agent-based model

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

$$M = \frac{AVG\ (PN + SN)}{7} \qquad (2)$$

If household agents have a high motivation level and feel responsibility, the psychological factor Perceived Behavioral Control (PBC) is considered. Households with high level (above the survey threshold) of *consideration* are tagged as "high intention" (C , Eq.3).

$$C = \frac{PBC}{7} \qquad (3)$$

2.2.2 Economic activation

The behavioral part of households' decision-making measured through the psychological factors is combined with a discrete economic decision model. The consideration of psychological factors is implemented through latent variables. These variables are expressed as a function of socioeconomic and personal attributes captured in our survey. In our discrete decision model, the latent variables explaining the behavioral part leave the likelihood function of a Logit mode choice model as a non-closed expression.

The decision model of the agents is based on random utility theory, which is the basis of several models and theories of decision-making in psychology and economics (Adamowicz 1998, McFadden 1974). According to random utility theory, among the three energy-efficient actions in our case a household chooses the one with the highest utility:

$$U_i^h = V_i^h + \varepsilon \qquad (5)$$

Where U being the total unobservable utility, V is representor of observable component (monetary), and ε representing the latent variables of an individual's decision (non- monetary). The monetary (*V*) part is consist of Technology cost (*T*), Service cost (*S*), saving Energy (θ^e), changes in energy Price (θ^p).

$$V_i^h = T_i^h + S_i^h + \theta_i^e + \theta_i^p \qquad (6)$$

The non-monetary (ε) part covers probability distribution that is specific to action (*i*) of household (*h*), and psychological preferences: Knowledge (*K*), Motivation (*M*), Consideration (*C*).

$$\varepsilon_i^h = P_i^h + K_i^h + M_i^h + C_i^h \qquad (7)$$

This leads to the following form of the utility function:

$$U_i^h = \sum V_i^h + P_i^h + K_i^h + M_i^h + C_i^h \qquad (8)$$

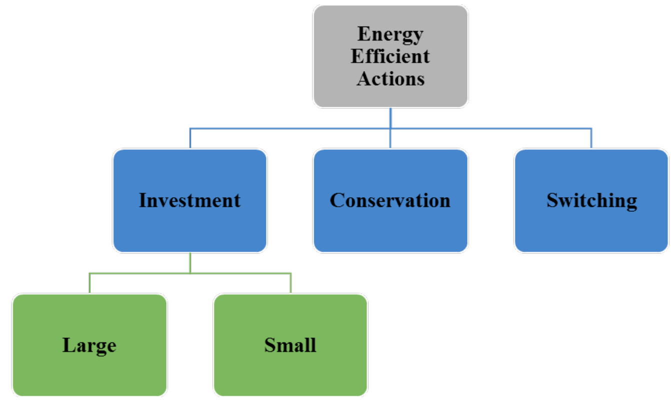

Fig. 2. Nested logit in the BENCH model

3. COMPUTABLE GENERAL EQUILIBRIUM MODEL (EU-EMS)

EU-EMS is a dynamic spatial general equilibrium model developed by the Netherlands Environmental Assessment Agency (PBL). It includes the representation of 62 countries of the world and the remaining Rest of the world region. The model's database has detailed regional dimensionality for EU28 countries and presents them as 276 NUTS2 regions. 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 (which is subject to trade costs), 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. The model includes New Economic Geography (NEG) features such as monopolistic competition, increasing returns to scale and migration.

EU-EMS could be used not only for the ex-ante impact assessment but also for ex-post impact assessment, other policy simulations and comparison between the policy scenarios. EU-EMS incorporates the following important features:

- linking regions within a New Economic Geography (NEG) framework;

- having inter-temporal dynamic features with endogenous growth engines;
- including detailed public sector interventions;
- incorporating a multi-level governance system.

Each European country in EU-EMS consists of several NUTS regions, which are connected by interregional trade flows of goods and services as well as interregional migration flows. Trade takes place between the regions of the same country as well as between the regions of two different countries. The pattern of interregional trade flows depends upon the preferences of consumers for buying goods from particular destinations and upon the prices of goods and associated transportation costs.

Each NUTS 2 region in EU-EMS includes various economic agents: several types of households, production sectors, regional and federal government. Households in EU-EMS are differentiated by five income classes which makes it possible to capture their specific consumption patterns and savings behaviour. Households with higher incomes consume more luxury goods and have higher savings.

Production and consumption in EU-EMS are associated with air pollution and generation of waste water and solid waste. EU-EMS includes all main types of greenhouse gas (GHG) and non-greenhouse gas (non-GHG) emissions and the associated damage valued in monetary terms. Waste can be treated differently in EU-EMS including deposit into land and water, incineration and recovery. Waste water can be cleaned and used again in the process of water production.

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.

EU-EMS is built upon the framework of Spatial CGE (SCGE) modelling and incorporates the representation of NUTS 2 regions. Within the SCGE framework the regions are connected by trade in goods and services, relocation of factors and economic activity and income flows. The trading of goods between regions is costly, as it is necessary to pay for the services of the national transport sector. This implies positive transportation costs. Transportation costs in EU-EMS are both good-specific and differentiated between the origin and destination regions.

The New Economic Geography (NEG) approach, emerged in the early 1990s and has gained much attraction for its arguments on centralizing and decentralizing forces in the geographic economic space, which could lead to convergence or divergence of regional incomes. In the NEG literature, initiated by the seminal papers of Krugman (1991) and Krugman and Vecchio (1995) , the idea of agglomeration economics, as suggested by Marshall´s externalities (Marshall 1920), and of cumulative causation, as initially proposed by Myrdal (1957), is revived. The central concepts of this theory are aggregate economies of scale, the home market effect and the existence of trade costs. As to the first, economic activity tends to concentrate in large-scale agglomerations not only because of internal returns to scale of the firm´s production, but also because of externalities which produce external returns to scale.

Producer contacts, and those to intermediary goods producers and customers, labour market pooling, and spill-over effects produce these externalities. As to the second, in the spatial context, economic activity will initially locate close to the place of market demand (home market effect). Together with the third central element, transport costs, agglomeration advantages and the home market effect can produce centralizing forces in the stage of modest economic integration. Only if transport costs, or market barriers, are sufficiently reduced, will a dispersion of economic activities set in.

Each region in the model is endowed with a certain level of labor, housing stock and natural resources. Labor/human capital stock in a region depends on its initial level in a chosen year and develops further according to human capital depreciation rate and new investments made by households and government. Human capital is differentiated between three types according to education level (low, medium and high).

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.

4. ABM-CGE INTEGRATED MODELING

4.1. ABM-CGE integration Architecture

The EU-EMS model is an advanced empirical CGE model capable of tracing comprehensive cross-sectoral effects.

BENCH is an empirical spatial ABM designed to quantify aggregate impacts of individual behavioural change where both psychological and economic factors play a role. We aim to integrate the two to leverage our ability to trace feedbacks between these processes at different scales. In particular, we use the agent-based BENCH model to zoom into the residential sector of CGE with the goal to investigates dynamics of energy demand (Figure 3). When modelling changes in individual energy demands in between annual equilibria of the CGE we explicitly trace changes in preferences and energy consumptions choices driven by individual assessments, pro-environmental attitudes and social interactions (non-monetary). This will result in the new budget shares a household spends on (i) energy vs other goods, and (ii) green vs. grey energy sources. These individual energy shares get aggregated at the provincial and national levels and may lead to changes in the consequently avoided carbon emissions. This process will result in new elasticities, which could serve as inputs to the CGE.

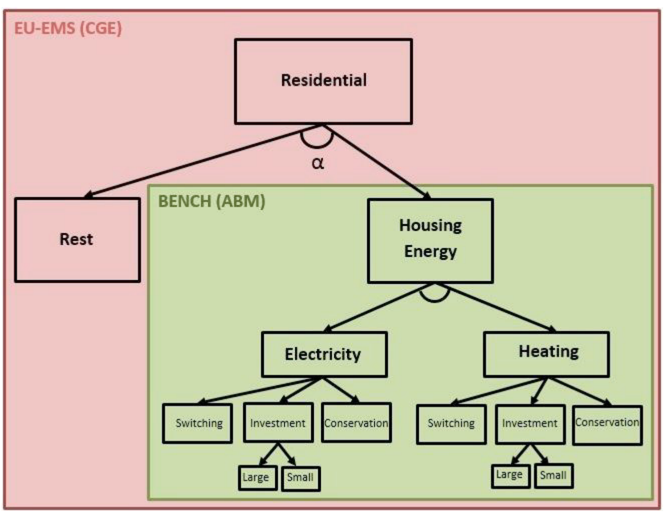

Fig. 3. ABM-CGE integration architecture

As illustrated in Figure 3, the agent-based BENCH model focuses on "Electricity" and "Heating" as the examples of households energy consumption. Households can reduce their carbon footprint by means of one of three actions: large and small investment on energy efficient devices and equipment (A11,A12); reducing energy consumption through behavioral change and conservation (A2); and by switching to low-carbon energy (A3).

4.2. Upscaling

With the help of Structural Equation and Latent analysis we come up with the probabilities to scale up households' energy efficient actions from provincial level (NUTS2) to country level (NUTS1). On the agent-level in BENCH we estimate the probabilities of choosing a particular action (i) based on households' socio-economic factors e.g. income groups (IG) and structural factors e.g. ownership statues (SF) in our empirical data (survey).

$$P_i^h = f(IG, SF) \qquad (9)$$

Then, inside CGE, based on the structure of the EU Household Budget Survey we scale up the output of the BENCH model (empirical grounded) by producing artificial population.

$$N_i = P_i^h \times P_{ij}^h \qquad (10)$$

4.3. Updates and Timelines

Figure 4 is illustrated the exchange variables and input/output of BENCH (ABM) and EU-EMS (CGE). We aim at integrating the micro and macro models to assure:
(1) direct feedbacks between behavioural change (non-monetary factors) and consequent changes in market shares of green vs. grey energy (within ABM),
(2) impacts of these on other economic sectors and carbon emissions (ABM => CGE), and
(3) accounting for non-residential electricity demand and changes in households incomes, structural factors e.g. ownership status, and population as economy evolves (CGE => ABM). The integration is implemented in two phases. The agent-based BENCH model runs annually and updates the CGE EU-EMS model each 5 years.

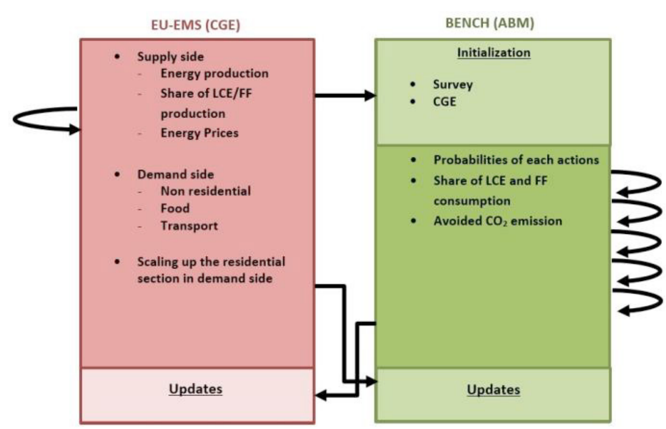

Fig. 4. ABM-CGE integration timeline and exchange data

5. DISCUSSIONS AND CONCLUSIONS

CEE systems are complex adaptive systems. There are several macro model that looking through this system with wide range of assumption and rationality. Yet, behavioral shifts among households are often modeled in a rudimentary way assuming a representative consumer (a group), a perfectly informed choice based on rational optimization, and instantly equilibrating markets. Going beyond a stylized representation of a perfectly informed optimizer requires a theoretically and empirically solid alternative (Niamir et al., 2018).

The potential of reducing emissions through behavioral change becomes even more important in the light of the Paris agreement (Niamir et al., 2018). We need to understand why and how individuals use energy. How do they respond to information about costs and benefits of energy choices? Even how do they interact in the environment? And importantly how do energy policies and programs can facilitate the transition to green economy that is less dependent on fossil fuels, and thus helps to mitigate global climate change. Yet, the conventional tools used to understand there system, such as system dynamics models, do not cope well with the complexity of consumer energy behavior (Farmer and Foley, 2009; Rai and Henry, 2016; Rai and Robinson, 2015; Wilkerson-Jerde and Wilensky, 2015). In addition, due to the complex nature of the system assessing the macro impact of these microeconomic dynamics in the system is intractable.

This research aims at exploring the feasibility of coupling models – macro with micro – to study climate change mitigation policy measures that target behavioral changes and are relevant at provincial and national levels. We present a methodology for macro-micro models integration by introducing the architecture of the BENCH agent-based model and EU-EMS CGE model integration in particular.

We present a work in progress. While the toy model is working (Niamir and Filatova, 2015) , we now have a unique opportunity to integrate two empirical models and improve the integration channels. When calibrate with the survey (for ABM) and Eurostat (for CGE) microdata-sets, such an integrated model can serves as a platform to test different climate-energy-economy scenarios. The exploration of uncertainty of this integrated modelling suit is a subject for future work .

ACKNOWLEDGEMENTS

This research was supported by the EU FP7 COMPLEX project No.308601. We would like to thank Hans Bressers from University of Twente, the Netherlands for his great supports. Leila Niamir also thanks Gregor Kiesewetter, Fabian Wagner, and Wolfgang Schöpp -YSSP2017 supervisory team- at International Institute for Applied Systems Analysis (IIASA), Austria, for their advises; and the Netherlands Organization for Scientific Research (NWO) who funded this YSSP2017.

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