Environmental Modelling and Software 134 (2020) 104839

Contents lists available at ScienceDirect

Environmental Modelling and Software

journal homepage: http://www.elsevier.com/locate/envsoft

Position Paper

Economy-wide impacts of behavioral climate change mitigation: Linking agent-based and computable general equilibrium models

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ARTICLE INFO

Keywords:
Behavior change
Grassroots dynamics
Soft linking
Environmental modeling
Upscaling
Computational economics

ABSTRACT

Households are responsible for a significant share of global greenhouse emissions. Hence, academic and policy discourses highlight behavioral changes among households as an essential strategy for combating climate change. However, formal models used to assess economic impacts of energy policies face limitations in tracing cumulative impacts of adaptive behavior of diverse households. The past decade has witnessed a proliferation of agent-based simulation models that quantify behavioral climate change mitigation relying on social science theories and micro-level survey data. Yet, these behaviorally-rich models usually operate on a small scale of neighborhoods, towns, and small regions, ignoring macro-scale social institutions such as international markets and rarely covering large areas relevant for climate change mitigation policy. This paper presents a methodology to scale up behavioral changes among heterogeneous individuals regarding energy choices while tracing their macroeconomic and cross-sectoral impacts. To achieve this goal, we combine the strengths of top-down computable general equilibrium models and bottom-up agent-based models. We illustrate the integration process of these two alien modeling approaches by linking data-rich macroeconomic with micro-behavioral models. Following a three-step approach, we investigate the dynamics of cumulative impacts of changes in individual energy use under three behavioral scenarios. Our findings demonstrate that the regional dimension is important in a low-carbon economy transition. Heterogeneity in individual socio-demographics (e.g. education and age), structural characteristics (e.g. type and size of dwellings), behavioral and social traits (e.g. awareness and personal norms), and social interactions amplify these differences, causing nonlinearities in diffusion of green investments among households and macro-economic dynamics.

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.[1] Academic and policy discourses highlight behavioral changes among households as an essential strategy for reducing GHG emissions and combating climate change (Dietz et al., 2013; Doppelt et al., 2009; Faber et al., 2012; McKinsey, 2009; Nielsen et al., 2020). Importantly, an individual's decision-making is known to deviate from rational and perfectly informed optimization process, calling for a thorough understanding of behavioral aspects (Abrahamse and Steg, 2011; Bamberg et al., 2015, 2007; Poortinga et al., 2004; Stern, 2016; van Raaij, 2017).

Policy-makers 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, 2014; JRC, 2014; Rive et al., 2006; Vandyck et al., 2016). CGE models are popular among governments and academia for ex-ante policy analysis. They rely on

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

https://doi.org/10.1016/j.envsoft.2020.104839
Accepted 6 August 2020
Available online 31 August 2020

advancements in micro-based macro-economic theory that represent the aggregate behavior of rational and fully-informed economic agents (households and firms) and their trade interactions via supply-chains. Behavioral changes, including behavioral climate change mitigation actions driven by the increased level of knowledge about climate change in society and shifts in preferences, are difficult to model directly with CGE models. This is one of the critics regarding their capacity to support climate change mitigation policy (Creutzig et al., 2018; Farmer et al., 2015; Farmer and Foley, 2009; Isley et al., 2015; Niamir et al., 2018b; Stern, 2016).

In contrast to this macroeconomic "top-down" approach, "bottom-up" agent-based models (ABMs) focus on behaviorally-rich representation of energy consumers, integrate technological learning, out-of-equilibrium dynamics and social interactions (Bhattacharyya, 2011; Farmer et al., 2015; Hunt and Evans, 2009; Niamir and Filatova, 2015; Niamir et al., 2018b; Tesfatsion, 2006). Agents in ABMs follow a set of if-else rules, sometimes combined with equations, that guide their actions, interactions with other actors or institutions (e.g. markets), and learning. ABMs could compliment macro-economic models by accommodating heterogeneity, adaptive behavior and interactions, bounded rationality, and imperfect information (Filatova and Niamir, 2019). However, their use for climate policy is hindered by high-data intensity for individual behavioral rules and interactions. When energy ABMs are grounded in empirical data, their upscaling remains limited (Humphreys and Imbert, 2013; Lamperti et al., 2019), preventing the assessment of economy-wide impacts, effects of national or EU policies and generalization of ABMs' results.

There is a long history in bridging top-down CGE models with bottom-up models (Krook-Riekkola et al., 2017), usually non-ABM. Specifically for energy, macroeconomic models are linked with engineering micro-simulation models focusing on the technological processes of electricity generation (Sue Wing, 2008). Scholars either establish a 'soft-link' between micro and macro models, or complement one by a reduced form of the other, or combine them directly through 'hybrid' modeling (Böhringer and Rutherford, 2009). Since engineering bottom-up models often rely on mathematical programming, the latter approach focuses on resolving mixed complementarity problems (Bohringer and Rutherford, 2008). Besides linking to engineering micro-simulations, national level CGEs rely on complimentary micro-simulation models for environmental analysis, taxation (Peichl and Schaefer, 2009), fiscal analyses (Debowicz, 2016) and labor market analysis (Benczúr et al., 2018). However, an integration of micro-macro approaches at the regional (sub-national) level is scarce (Verikios and Zhang, 2015). In parallel, as inequality and distributional impacts of climate change policies come into a spotlight internationally, introducing heterogeneity into CGE models becomes increasingly important (Bijl et al., 2017; Kulmer and Seebauer, 2019; Melnikov et al., 2017; Rao et al., 2017; van Ruijven et al., 2015). This is commonly done by disaggregating the representative agent in macro models with micro-level survey data (Rausch et al., 2011). Duarte et al. (2016) provide an excellent example on modeling of pro-environmental consumer behavior in a regional CGE model for Spain using micro-level data. This study evaluates the impact of improving environmental awareness by specifying drivers of behavioral changes – adoption of household appliances with different energy efficiency levels – for different income levels using household survey data (Duarte et al., 2016). While using survey data in CGEs is a major step in accommodating heterogeneity, the choices that economic agents pursue remain fixed and are still assumed to be taken under conditions of perfect information. It hinders the representation of behavioral changes, bounded-rationality and social influences so prominent in understanding pro-environmental choices (Niamir et al., 2020a; Steg and Vlek, 2009).

Linking macroeconomic CGE models with micro-level behaviorally-rich ABMs can operationalize behavioral changes in formal policy analysis and open new synergies between micro and macro approaches (Krook-Riekkola et al., 2017; Melnikov et al., 2017; Parris, 2005; Safarzyńska et al., 2013; Smajgl et al., 2009). Earlier attempts to integrate ABM and CGE models include the work of Safarzyńska et al. (2013) who propose an elegant way to integrate the evolutionary dynamics of ABMs into a CGE model. Yet, authors leave it at the conceptual level without an implementation. Smajgl et al. (2009) discuss a farm-level integration of ABM-CGE for fishery policy impact assessment, with no integration results. To the best of our knowledge, there is no empirical example of resolving the key methodological differences between ABM and CGE modeling while aligning with survey data on behavioral heterogeneity.

The current paper addresses this methodological gap by demonstrating how aggregated impacts of household energy behavior changes emerging from an empirical ABM could be scaled up and linked to the macroeconomic dynamics of a CGE model. To demonstrate the feasibility of the method we employ a soft-linkage between the two empirical models; future work will focus on a hard-link integration following our earlier pilot on using software wrappers to assure a real-time data exchange between toy ABM and CGE models (Belete et al., 2019). Here we ensure models' consistency by aligning functional forms and by using the same database and economic scenarios. The objective of this paper is twofold: (1) to investigate feasibility of an original approach to link empirical ABM and CGE models while targeting individuals' heterogeneity, social interactions, and behavioral changes; and (2) to explore the impacts of climate change mitigation behavior across scales, from individuals to the EU regions. Towards this end, we propose a three-step upscaling approach that goes beyond our specific application and may serve as a systematic way to link ABM and CGE models (Section 2). Our results demonstrate that it permits tracing the macro-economic and cross-sectoral impacts and indirect effects of individual energy behavioral changes (Section 3). Section 4 concludes with a discussion and outlining future work.

2. Methods

To explore economy-wide impacts of behavioral changes and the role of social interactions the current paper employs the strengths of micro and macro socio-economic models. We use an empirical behavioral ABM (*BENCH-v.3*) originally developed to study cumulative impacts of individual changes in energy use (Niamir et al., 2020b, 2018a). To trace indirect effects and cross-sectoral impacts of shifts in residential energy demand and changes in households consumption behavior, we employ an empirically-calibrated CGE model (EU-EMS) (Ivanova et al., 2019).

The scientific challenge is in aligning the two models that differ in key assumptions. Namely:

- **Representative vs. heterogeneous agents**: CGE models work with a representative agent (group) while ABMs assume heterogeneity in attributes and behavior;
- **Perfect vs. bounded rationality**: agents in CGE are assumed to be fully rational while ABMs proliferate in tackling research problems where bounded rationality is relevant;
- **Static vs. adaptive behavior:** households in CGE have fixed preferences and perfect information, while ABM are designed to explicitly model adaptive expectations. Since ABM-agents do not have full information, they **learn** over the course of a simulation, either from their own experience, from their social network or through market signals;

Fig. 1. Households' choices in the spatial BENCH agent-based model.[3].

- **Unique one shot equilibrium, vs. out-of-equilibrium dynamics:** CGE models are solved via the assumption of a unique equilibrium occurring in one shot when markets clear. In contrast, ABMs trace the process of out-of-equilibrium dynamics and transitions between multiple equilibria while eliciting path-dependencies.

2.1. Models and scenarios

2.1.1. The BENCH agent-based model

Originally, the *BENCH* ABM (Niamir et al., 2020b, 2018a; Niamir and Filatova, 2017) was developed to investigate the role of behavioral changes with respect to an individual energy use in the transition to a low-carbon economy. Households in *BENCH* ABM 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 behavioral factors (e.g. awareness, personal norms, social norms). BENCH is spatially explicit, with behavioral rules of agents calibrated based on the survey data for two EU NUTS2[2] regions: Navarre, Spain and Overijssel, The Netherlands (Niamir et al., 2020a).

We advance this ABM further to permit integration with the EU-EMS CGE both in terms of the theoretical consistency of functional forms used in ABM and CGE as well as the datasets and scenario assumptions. We start aligning the ABM model with its macro counterpart by including the empirically estimated discrete choice functions for the representation of households' investment decisions. These functions stem from the utility optimization approach that is also used for the derivation of demand functions in the CGE model and are further relaxed in the ABM to accommodate bounded rationality. Namely, agents' utility functions are modified to align with empirically-grounded energy decisions from the households' survey (Niamir et al., 2020a), social interactions and learning – with macroeconomic dynamics in our data-driven CGE model. In particular, *BENCHv.3* focuses on energy investments that households may decide to undertake: significant investments in house insulation (I1) or moderate investment in solar panels (I2), and modest investments in energy-efficient appliances (I3) (Fig. 1).

Cognitive process behind individual behavioral changes: in accordance with the Theory of Planned Behavior and Norm Activation Theory from psychology, we assume that boundedly rational individuals in *BENCH-v.3* make decisions following a number of cognitive steps: knowledge activation, motivation, and consideration (Niamir et al., 2020a, 2018a). Fig. 2 shows heterogonous households in sociodemographic characteristics, dwelling conditions, electricity and gas consumption follow a cognitive process to decide whether to pursue any energy investment (I1–I3). Niamir et al. (2018a) describes how each individuals knowledge activation and motivation are measured and calculated at the model initialization stage based on the survey data. In summary, an individual knowledge activation level is calculated based on the average of three types of knowledge - person's climate-energy-environment knowledge (K), awareness about climate, environment and energy issues (A_C), and energy decision (A_E). If this average for an individual is above the empirical threshold, then the person is tagged as "feeling guilt" and proceeds to the next step to assess his/her motivation for actions I1–I3. Such individuals proceed to evaluate the motivational factors: personal and social norms (N_P, N_S) for each action (I1–I3). If individuals are highly motivated and "*feel responsible*", the perceived behavior controls[4] (*PBC*), and the 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.

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.

$$V_{ij} = \sum x_{ij}\beta_i + \varepsilon_{ij} \qquad \text{(Eq. 1)}$$

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 behavioral factors – and the parameter vector (β_i) estimated using a probit regression (Niamir et al., 2020a). Finally, ε_{ij} is the vector of error terms. An individual chooses a particular sub-action (i) when their utility is non-negative:

$$If\ V_{ij} \geq 0 \quad \left(I_{ij} = True\ \ else\ I_{ij} = False\right) \qquad \text{(Eq. 2)}$$

Social interactions and learning: The speed of green investments diffusion does not depend only on social interactions that affect updating of knowledge, awareness and norms. It depends also on the individual heterogeneity: socio-economic characteristics or dwelling

[2] The Nomenclature of territorial units for statistics, abbreviated NUTS is a geographical nomenclature subdividing the economic territory of the European Union (EU) into regions at three different levels (NUTS 1, 2 and 3 respectively, moving from larger to smaller territorial units).

[3] Photo sources: I1 by Tracey Nicholls (CC BY 3.0); I2 by Enrix-Knuth (CC BY-SA 4.0); I3 by Tommaso.sansone91(CC0). Available from: https://commons.wikimedia.org.

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

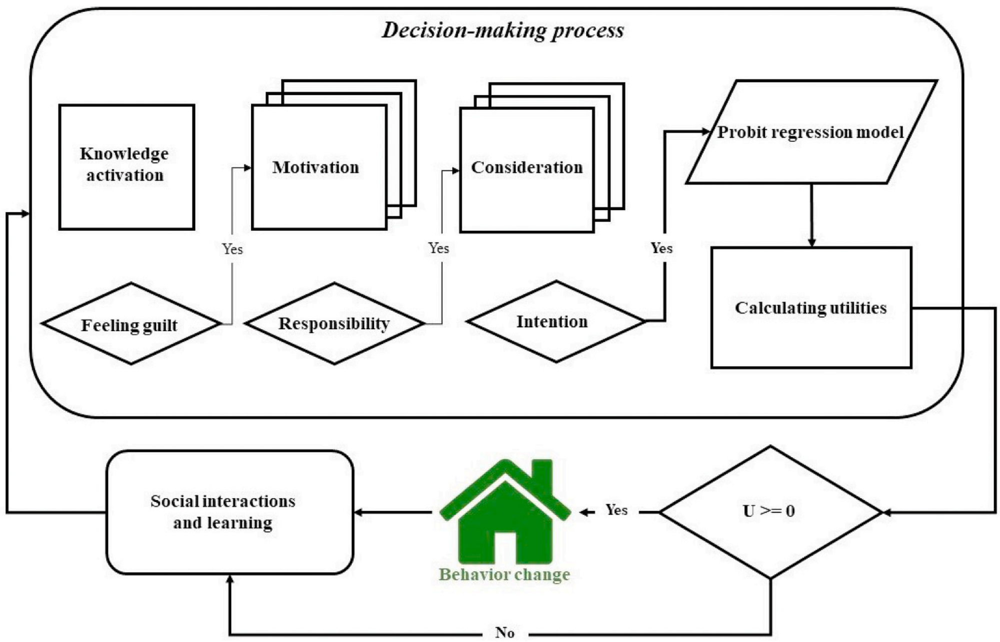


Fig. 2. BENCH-v.3 ABM structure: cognitive process behind individual behavioral changes (I1–I3).

characteristics, which affect utility of taking an action I1–I3 (i.e. serve as proxy for the perceived behavior control, *PBC*). In *BENCH-v.3*, agents exchange information following a simple opinion dynamics model (Moussaïd et al., 2015). When a neighbor 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 behavioral factors (K, A_C, A_E, N_P, N_S, PBC) with those of their closest neighbors, and gradually adjust them (Fig. 3, Eq. (3)). We run various scenarios of this social learning (see section 2.1.3).

Our ABM uses the same baseline scenario of regional demographic and economic development as the CGE model ensuring the consistency between the scenario analysis in two models. Further, the ABM takes as inputs data on the regional GDP projections estimated for 2015–2050 by the CGE model. The detailed description of the *BENCH* agent-based model is presented in Appendix 1.

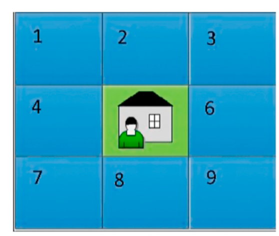


Fig. 3. Social dynamics and learning in a neighborhood where an individual undertook an action at time t.

$$X = \{K_n, A_{C_n}, A_{E_n}, N_{P_n}, N_{S_n}, PBC_n\} \quad , \quad n = \{1, \ldots 9\}; \qquad \text{(Eq. 3)}$$

$$If\ Max\left(mean\left(X_n^t\right),\ median\left(X_n^t\right)\right) \geq X_j^t \quad \left(X_j^{t+1} = X_j^t + 0.02 \cdot X_j^t\right)$$

2.1.2. Computable general equilibrium model

EU-EMS (Ivanova et al., 2019) is a spatial CGE model developed by the PBL Netherlands Environmental Assessment Agency for policy impact assessments. The current version of EU-EMS covers 276 NUTS2 regions across the EU28 member states. Goods and services are produced by firms and consumed by households or other firms and exchanged on competitive markets. Spatial interactions between regions are captured through the trade in goods and services, factor mobility, and knowledge spill-overs.

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 behavior 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.

The database[5] 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.[6] 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 panel data econometric analysis and estimations that have been done for Total Factor Productivity (TFP) projections using the EU-KLEMS database.[7] We have used panel data techniques on EU-KLEMS data in order to model the development of TFP according to the technological catch-up theory. The detailed description of our CGE model is presented in Appendix 2.

Measuring economic inequality: economists often measure regional disparities using Theil's T inequality index (Eq. (3)), the

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

[6] http://viewer.etisplus.net/.

[7] http://www.euklems.net/.

Table 1
Micro-level end-user behavioral scenarios. Source: BENCH.v3

Behavioral scenarios	Social dynamics	Definition
Baseline	Slow *In an active neighborhood: individuals interacts with a maximum of four neighbors*	Individuals with the value of their behavioral attributes – components shaping awareness and motivation – lower than that of their neighbors adjust by increasing the value of by 2%[a] (see Eq. (3)).
FD **(Fast Dynamics)**	Fast *In an active neighborhood: individuals interacts with all available neighbors*	Individuals with the value of their behavioral attributes – components shaping awareness and motivation – lower than that of their neighbors adjust by increasing the value of by 2% (see Eq. (3)). This scenario represents a rapid bottom-up diffusion of pro-environmental social norms driven by households alone without any policy support.
ID **(Informative Dynamics)**	Informative *In an active neighborhood: individuals interacts with all available neighbors* + *Intense information policy*	This scenario assumes an intense information policy – e.g. social advertising and the promotion of pro-environmental behavior – that raises the level of knowledge and motivation across the entire population. Hence, at initialization all households agents start with 2% higher values of behavioral attributes, before engaging in any social learning. The ID scenario highlights the importance of information diffusion and information campaigns focusing on behavioral climate mitigation. It assumes that all individuals do update their knowledge and motivation when an information policy applies.

[a] As an ABM the BENCH model permits experimentation with numerous "what if" scenarios. Exploring the entire space of complex adaptive models, such as BENCH, is a massive research project on its own (Kwakkel and Pruyt, 2013). We tested different level of diffusion ranging from 1% to 4% and choose 2% since it captures the qualitative trend anticipated by experts. For example, the higher level of diffusion generate more active neighborhoods in earlier years converting all households to became energy-efficient between 2035 and 2040, but that does not resemble the narratives in the literature (Allen et al., 2018; Creutzig et al., 2016; Grubler et al., 2018; IPCC, 2014). Exploring the entire parameter space would be an interesting topic for future research.

absolute value of which indicates the distance from equality.

$$Theil\_T = \frac{\theta_i}{\sum_i \theta_i} \sum_{i=1}^{N} \log\left(\frac{\gamma_i}{\mu}\right) \tag{Eq. 3a}$$

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 *EU-EMS* CGE model estimates the cross-sectoral aggregated impacts of individual behavioral changes produced by the ABM, and traces the consequent changes across the EU regions triggered by the macro economy. The CGE receives measures: a) the diffusion of each of the three types of actions (I1–I3) among heterogeneous households (classified in 12 age and education groups); b) the changes in electricity and gas consumption; c) saved CO_2 emissions; and d) the amount of investment from BENCH model results.

2.1.3. Scenarios

Micro-level end-user behavioral scenarios: besides being heterogeneous in terms of sociodemographic characteristics (e.g. age, income, education), housing they reside in (e.g. tenure status, size, energy label), and psychological factors (e.g. attitudes and beliefs, personal norms), agents in the *BENCH-v.*3 ABM exhibit heterogeneous behavioral characteristics, such knowledge and awareness, engage in social interactions and learn. *BENCH.v3* ABM introduces three end-user behavioral scenarios (*Baseline, FD, ID*) by differentiating between the intensity of social interactions and the speed of learning (see Table 1). Based on the neighborhood size, this social learning may occur at either a slow or fast pace (see scenarios in Appendix 1).

Macro-level scenarios: in addition to these three behavioral scenarios, the EU-EMS CGE model relies on the demographic projections from Eurostat until 2050 and Total Factor Productivity (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 of micro-level behavior with respect to energy-related investments of heterogeneous households.

2.2. Upscaling behavioral changes

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 in a systematic manner, we take a step-wise approach to bridge the ABM with the CGE model (Fig. 4).

2.2.1. Step 1: from individual households to regional shifts in energy use

*BENCH-v.*3 ABM calculates the extent of behavioral changes among heterogeneous household agents who evolve through a cognitive process (section 2.1.1, Fig. 2) before reaching a more rational stage where the discrete-choice utility maximization is activated (section 2.1.1, Eqs. (1) and (2)). Given the stochastic nature of ABMs, we use the mean values from 100 ABM simulations run for each scenario and case-study to feed them further into the CGE model. The main outcomes of the *BENCH-v.*3 ABM used in the *EU-EMS* CGE model are the relative changes in electricity and gas use and the total investments made by various individuals (I1–I3). The *EU-EMS* CGE model, however, operates at the level of all 276 EU28 NUTS2 regions, and needs regional changes in energy consumption and investments of the representative households as an input. Hence, the behavioral 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 (see next steps and Fig. 4).

2.2.2. Step 2: Dynamic socio-demographic groups with similar behavioral patterns

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. Economic theory suggests that investment choices depend on households' incomes. However, our survey on behavioral changes regarding energy use (Niamir et al., 2020a) reveals that age and education are the most important factors explaining households preparedness to invest in low-carbon energy (I1–I3).[8] Thus, we define behavioral patterns for a group of households in the Dutch and Spanish regional ABMs separately, aggregating by age and education

[8] With the help of our empirical data, we examined the impact socio-demographic factors, namely income, gender, education and age, on households energy bahavior changes in two provinces (Overijssel, NL and Navarre, ES). Particulary, our analysis shows the probability of households energy behavior increases with the level of eduction (95% confidential interval) (Niamir et al., 2020a).

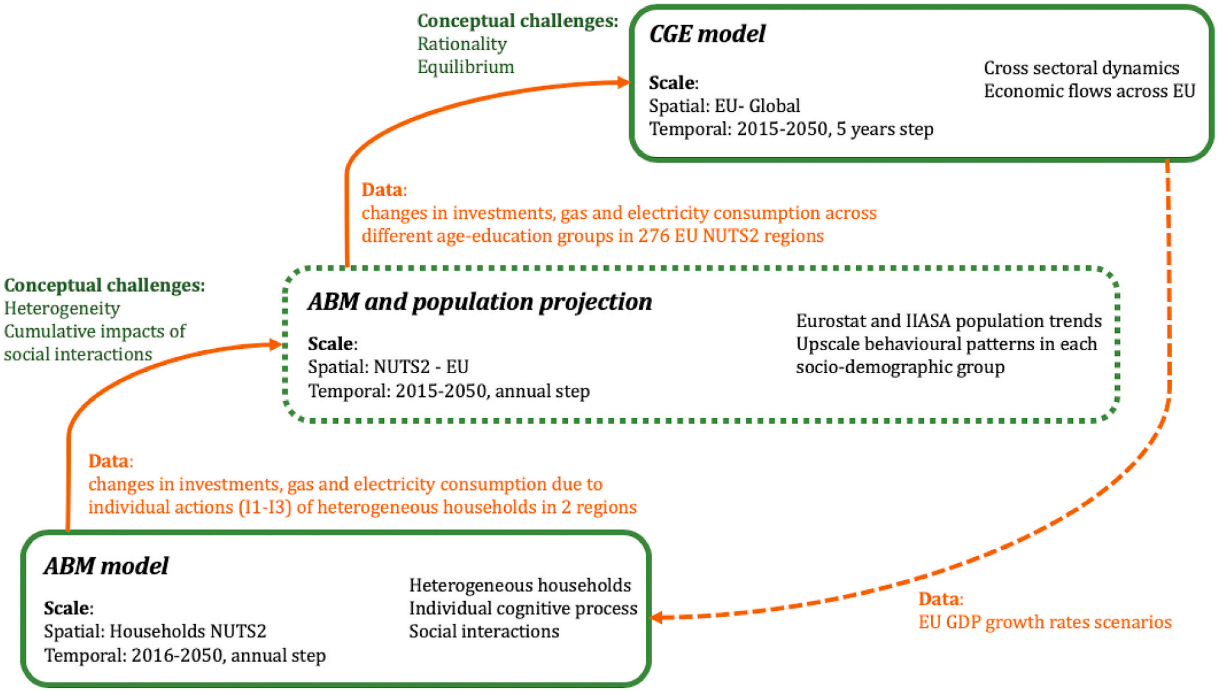


Fig. 4. Upscaling individuals behavioral change via linking ABM and CGE models.

Table 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)

level. Following the Eurostat classification, we work with 12 age-education groups (Table 2).

For all 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 behavioral factors –awareness, motivations, intentions and likely actions– across 12 groups differ between the two countries in our survey sample, and so do the patterns of behavioral climate change mitigation emerging in the ABMs. To utilize the information regarding regional differences in patterns of behavioral change, we create the mapping between NUTS2 regions of the EU28 with the two ABM regions according to their perceived cultural distance. Social structure, wealth and lifestyle, religion, institutional and economic conditions, and natural environment play a role in assessing cultural distance (Gobel et al., 2018; Hofstede, 2011, 2001; Kaasa et al., 2016; Schwartz, 2014; Vignoles et al., 2018). Specifically, in the absence of more granular data, we use the Dutch case to approximate how the behavioral patterns may evolve in the North-West EU states, and the Spanish case – for the South-East EU states (see Table A3.1 in Appendix 3). We acknowledge that this approach does not fully capture all the cultural differences but it, for example, accounts for the role of social network (higher among the Spanish respondents compared to the Dutch) in behavioral climate change mitigation. Ideally, one should use native survey data regarding the modeled behavior or employ secondary data on revealed empirical differences on behavioral changes across regions. Furthermore, differences in policy, institutional, technological, and environmental conditions across EU countries are indirectly accounted for in our CGE model and the databases it relies upon.

Since behavioral 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[9] 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 scenario projections[10] 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 behavioral patterns of 12 groups in our ABM. Hence, now we use age and education information to linked it with the emerging behavioral patterns of the agent-based BENCH v.3 model when creating NUTS2 specific – that is, corresponding to the population structure of that region – inputs into the spatial EU-EMS CGE model.

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

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

2.2.3. Step 3: Cumulative economy-wide impacts of behavioral changes

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 behavioral changes among heterogeneous households at the level of 276 EU28 NUTS2 regions. This allows us to understand the impacts of various behavioral 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. Data flows between two models are presented in Fig. 4.

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 behavioral 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 behavior heterogeneous across the 12 groups.
- **From perfect to bounded rationality**: Agents in our ABM are boundedly rational due to the presence of behavior factors (*K*, A_C, A_E, N_P, N_S, *PBC*) that precede discrete choice utility estimate: subjective knowledge and awareness, motivation, and intention to consider a change in behavior, which are all prone to social influence. The use of the ABM allows us to assess the impacts of pure behavioral 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 labor 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 CGE model.
- **From static to adaptive agents**: Agents in the ABM are prone to social influence and learn from their neighbors. As their behavior attributes – knowledge and awareness – evolve, they go through various cognitive stages of knowledge activation, motivation and consideration and may eventually decide to invest in low carbon energy. By scaling up these behavioral patterns through age-education groups, we are able to link to the architecture of a CGE. By default CGE models assume perfect information and rational expectations, omitting a variety of behavioral strategies through which adaptive behavior can be channeled into macro dynamics.
- **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.

Before discussing the results, it may be useful to be explicit about the limitations of the current study. The presented CGE-to-ABM link is currently indirect, operationalized via the EU GDP growth rates scenarios (the dotted curve in Fig. 4). Furthermore, to demonstrate the applicability of method, we work with two survey datasets; for a real policy analysis it is essential to work with a richer representation of regions that may also account for differences in climatic and institutional conditions across countries. While our ABM relies on households' surveys (Niamir et al., 2020b, 2020a; 2018a) for micro-validation, macro-validation against regional-level panel data remains a subject of future work. We believe that micro-validation is sufficient for the methodological demonstration of the applicability of this approach for upscaling behavioral climate change mitigation. Complementing it with macro-validation would be essential when performing a real policy analysis.

3. Results and discussion

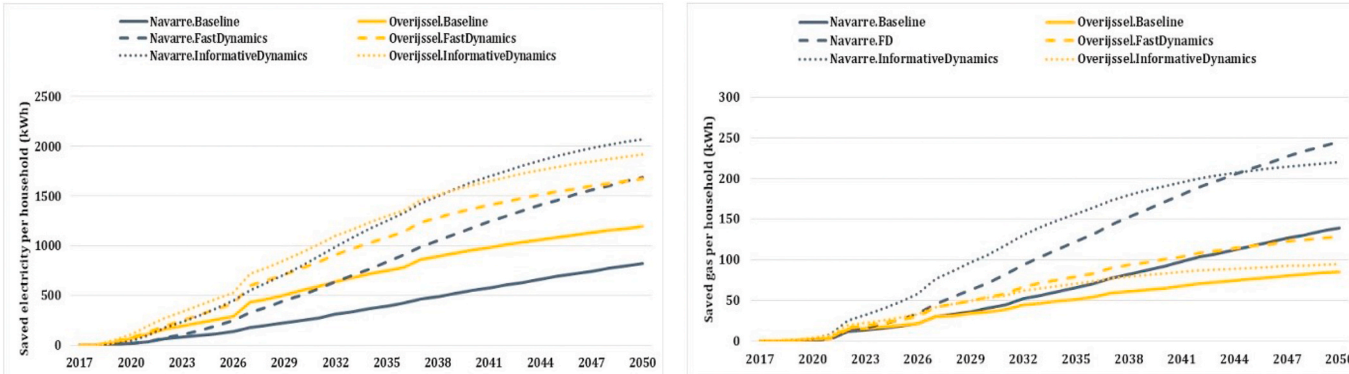
Given the stochastic nature of ABMs, we run *BENCH* multiple times under the same parameter settings for each scenario. The ABM results presented below plot the means across 100 random runs. Therefore, we use the mean values from each ABM scenario and case-study to scale up the observed behavioral patterns and to estimate their cross -sectoral impacts in the CGE model.

3.1. Step 1: From behavioral patterns in survey data to cumulative impacts in two provinces

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

Fig. 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 a and Table 3). 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 a and Table 3). However, these trends do 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. 5b) and the opposite effect in Overijssel (*ID* delivers 26% lower gas savings compared to *FD*, Fig. 5b). The difference between cases may be driven by initial conditions (climate, institutional settings, gas prices) in the two countries. In addition, comparing *FD and ID* scenarios shows that an information policy and social interactions among neighbors impact households' insulation decisions in a non-linear way.

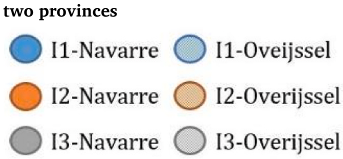
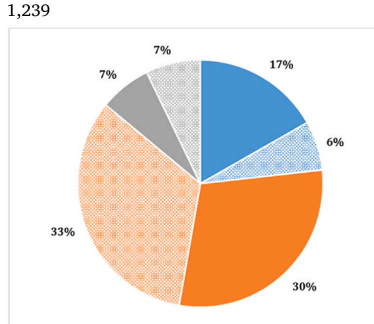
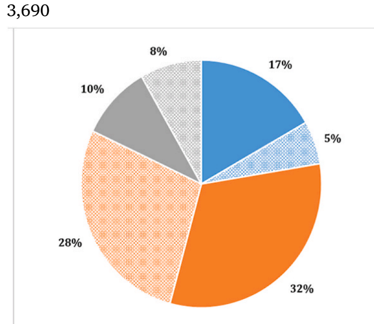
Table 3 shows the amount of CO_2 emission savings that households' energy behavior changes could deliver, and at what investment cost. Intensive social interaction (*FD* scenario) leads to 1.4 and 2 times more saved CO_2 emissions in Overijssel and Navarre compared to the *Baseline*. As expected, information 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 behavioral 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–I3) unequally distributed over time and space. These results are a pure effect of individual changes driven by behavioral factors: we do not include any price-based



(a) electricity (b) gas

Fig. 5. Saved energy (kWh) per household as a result of investment (I1–I3) under three behavioral scenarios in two EU provinces over 34 years (2017–2050). Source: BENCH-v.3.

Table 3
Saved CO_2 and household investment in two provinces (Overijssel and Navarre) under three micro-level behavioral scenarios over time. We report the mean value across 100 runs under each scenario. Source: BENCH-v.3 ABM.

	Scenarios	Provinces	2030	2050
Saved CO_2 emission (tons per household)	**Baseline**	Overijssel	0.50	1.09
		Navarre	0.23	0.78
	FD	Overijssel	0.71	1.53
		Navarre	0.47	1.59
	ID	Overijssel	0.75	1.93
		Navarre	0.85	1.75
Total investments (in 2016 Euro per household)	**FD**	Overijssel	2,908	6,858
		Navarre	2,198	8,020
	ID	Overijssel	2,578	5,430
		Navarre	2,931	7,585
The share of preferred actions (in percentage)		Overijssel	I1:4.9% I2: 26.1% I3: 69%	I1:4.0% I2: 20.1% I3: 75.9%
		Navarre	I1:12.1% I2: 26.7% I3: 61.3%	I1:9.4% I2: 22.5% I3: 68.1%
Total number of actions		Overijssel	2,839	6,875
		Navarre	1,239	3,690
Investments in 2016 Euro per action, % of total invested money in two provinces 				

scenarios (subsidies for green or taxes on grey energy) or changes in technological costs in this article.

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*).

3.2. Step 2: Scaling-up behavioral scenarios to national and EU level

After analyzing the dynamics in households' behavioral changes in two provinces over time, we switch to understanding how they change over space. Using the population projection scenarios for the EU28 (see section 2.2, step 2), we scale the dynamics in household energy behavioral changes in two provinces over time up to national and EU levels. Namely, we define behavioral patterns for a heterogeneous group of households in the Dutch and Spanish regional ABMs. For each of the 12 age-education groups (Table 2), a number of households perusing an action (I1–I3) is estimated together with the average investments, and

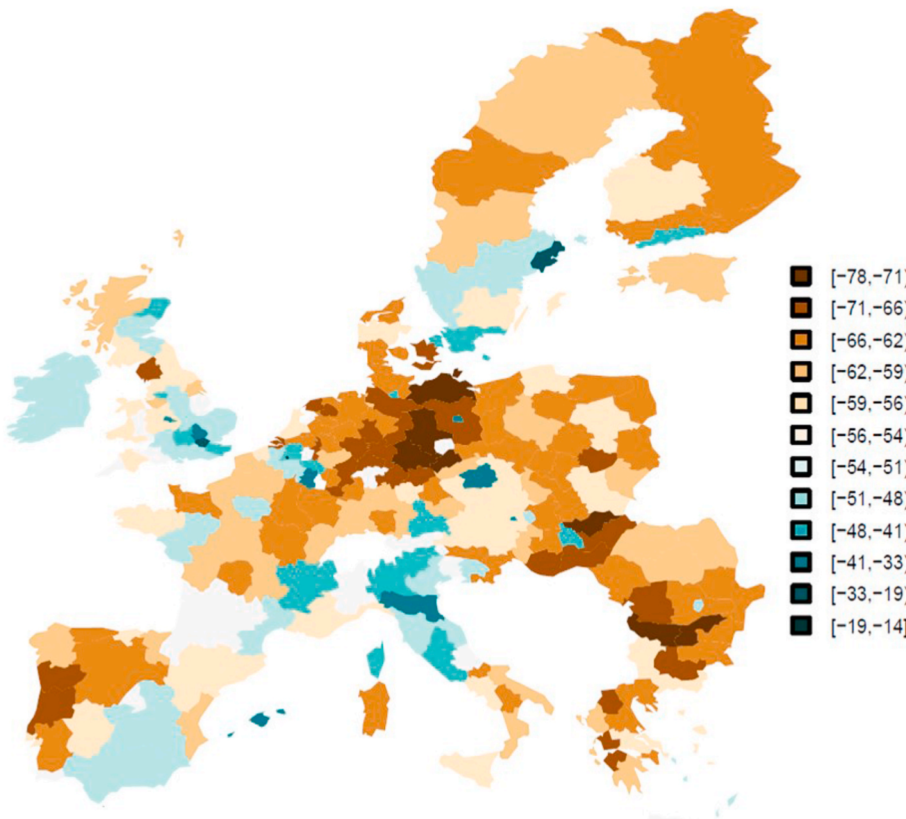


Fig. 6. Percentage change in electricity consumption in 2050 from the base 2015, calculated as a result of scaling up the outcomes of the ABM model with population changes in the "Fast dynamics" scenario. Source: scaled-up BENCH-v.3 results.

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 behavioral changes decreases between 51 and 71% (the Netherlands) and 51–66% (Spain) by 2050 (see Appendix 4, Table A4.1).

Fig. 6 shows percentage changes in 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 behavioral 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 behavioral changes diffuse and what regions emerge as laggers or pioneers in bottom-up investments in energy-efficiency. If behavioral 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.

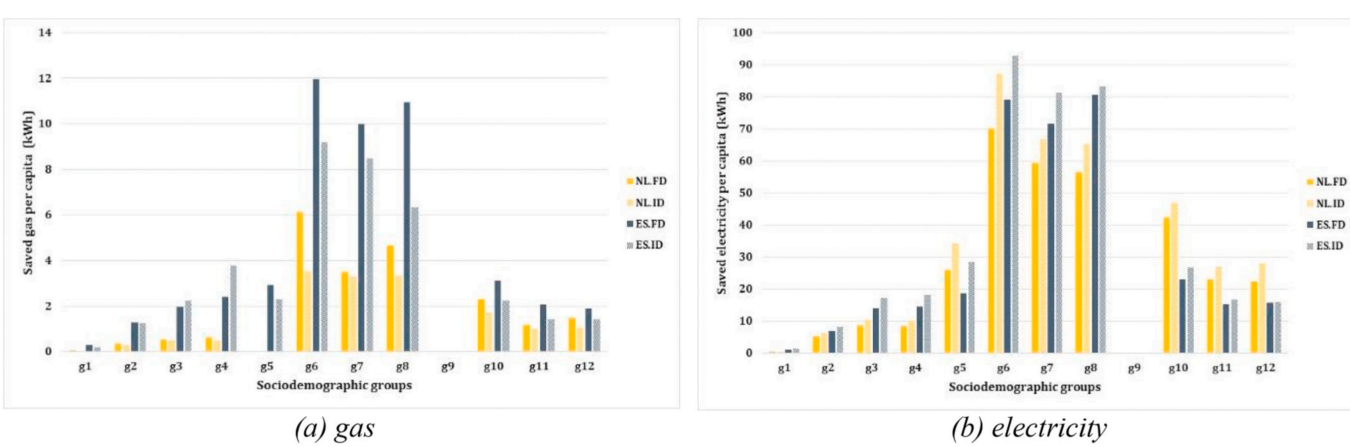


Fig. 7. Saved energy per capita (electricity and gas) as a result of households' energy investments among 12 sociodemographic groups (Table 2) under behavioral scenarios (FD,ID) in two countries. Source: EU-EMS and BENCH-v.3.

3.3. Step 3: From regional to the national and EU28 economy

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 2). The ABM-CGE results indicate that households with higher education levels are more likely to change their behavior 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 (Fig. 7). Among the pioneers (g6-8, i.e. middle educated and 20+ age; see Table 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 behavioral scenarios. Intensive social dynamics (*FD* scenario) has a stronger impact on saving gas, while the informative *ID* scenario activates more households in saving electricity. Appendix 4 presents a more detailed ABM-CGE analysis on diffusion of households' investment per capita per action among sociodemographic groups.

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. Depending on households' consumption patterns, such shifts in consumption might result in higher values of GDP over time.

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 behavioral scenarios on real GDP that is GDP that includes only quantity effects. We choose to use GDP in our analysis instead of welfare indicators such as equivalent variation measure because the monetary indicator such as GDP can be easily compared with the outcomes of the ABM model in terms of monetized energy savings and investments. The focus of the present study is in illustrating the added-value of the use of CGE model and the degree of the indirect and economy-wide effects calculated by the CGE which justifies the choice of monetary GDP indicator for our analysis. Fig. 8 illustrates the difference in regional real GDP levels in 2050 between the *Baseline* and *FD* scenarios. Most of the EU28 regions benefit from the behavioral changes, which leads to a decrease in energy consumption, with a few regions affected negatively. The level of overall real GDP impacts depends on the size of the region in terms of population and its share of highly-educated youth. Appendix 4 presents the percentage changes on the level of regional GDP relative to the *Baseline* scenario (see Figures A4.2).

Fig. 9 presents the effects in relative terms (scenario as % of the baseline which already accounts for whether a region is rural or urban) and relate them to GDP per capita. It implies there is a statistical relationship between the two variables: 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 modeled behavioral changes. Though the relationship is non-linear, the trend indicates that rich and economically well-developed regions receive higher benefits from promoting behavioral changes in the long-run compared to the lagging regions.

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. To understand how behavioral changes under our scenarios impact EU28 regional disparities, we calculate economic inequality index for the period 2015–2050 (section 2.1.2, Eq. (3)). 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

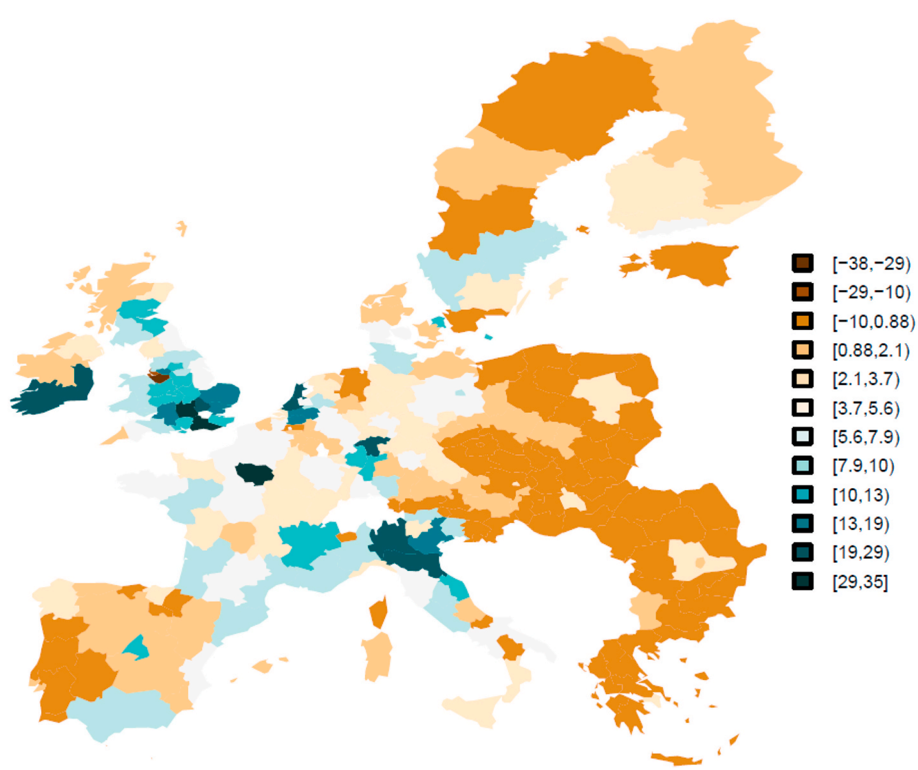


Fig. 8. Deviation in the levels of regional real GDP under the "Fast dynamics" scenario compared to Baseline in 2050 as an aggregated effect of households' behavioral changes, in millions of Euros. Source: EU-EMS and BENCH-v.3.

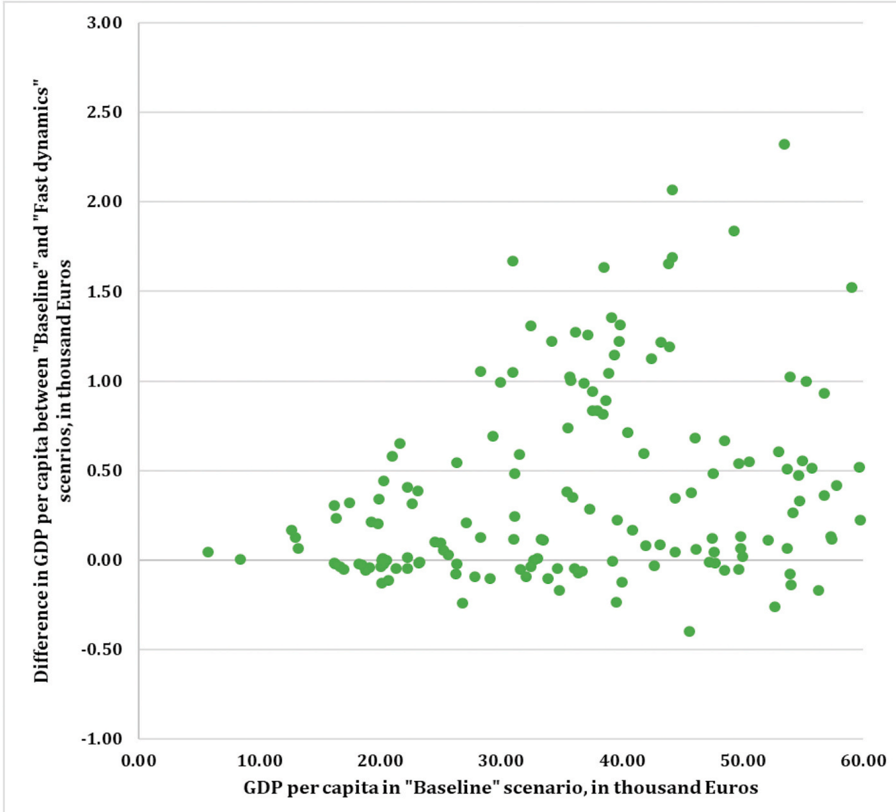


Fig. 9. Correlation between changes in GDP per capita under “Fast dynamics” scenario and the level of regional GDP per capita under “Baseline” scenario in 1000 Euros per individual in 2050. Source: EU-EMS and BENCH-v.3.

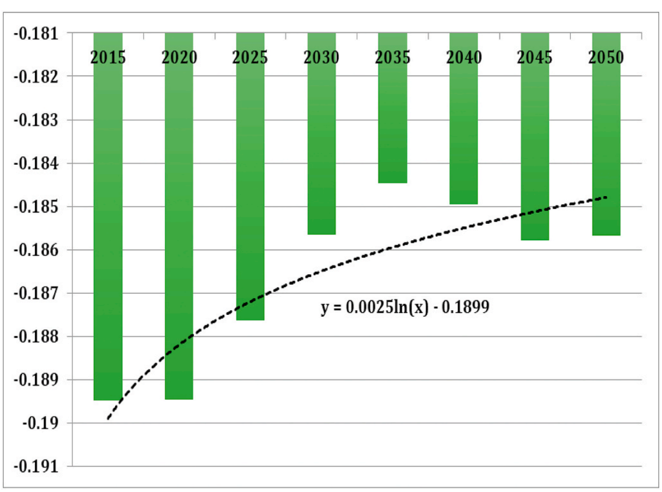


Fig. 10. Dynamics of the Theil-T income inequality index over time under “Fast dynamics”. Source: EU-EMS and BENCH-v.3.

process (Fig. 10). However, the regional inequality in 2050 does not reach the level of 2015, indicating the positive overall impact of behavioral changes on equality. Despite this, changes in inequality due to the implementation of behavioral scenarios remain modest.

4. Conclusions and outlook

The potential of individual behavioral changes in reducing carbon emissions attracts considerable attention as one of the climate change mitigation strategies (Creutzig et al., 2016; IPCC, 2014; Niamir, 2019). 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 behavior, making it difficult to integrate behavioral 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 behavior and interactions, bounded rationality, and imperfect information (Rai and Henry, 2016). While there are few (largely non-empirical) ABMs in policy and institutional domain that take a macro, e.g. country and global scale perspective (Castro et al., 2020; Gerst et al., 2013), behaviorally-rich empirical ABMs mostly operate on small scales of neighborhoods, cities, and regions. Although these micro ABMs are strong in aggregating heterogeneous adaptive behavior, they omit feedbacks with the rest of the economy and cross-sectoral impacts. Survey data is increasingly used to specify individual agent’s rules, yet this behavioral data is not always compatible with the data used in macro models. Linking ABMs and CGE models could ameliorate their weaknesses. Yet, the models should be aligned coherently conceptually and data-wise to benefit from their strengths (Voinov and Shugart, 2013). 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 insights from this methodological exercise offer three conclusions. Firstly, we demonstrate the feasibility and importance of introducing heterogeneity and behavioral-rich dynamics in assessing climate change mitigation policies. We develop a transparent step-wise process to integrate an empirical behaviorally-rich ABM and a spatial CGE model. To the best of our knowledge, this is the first attempt to link empirical ABM and CGE models to estimate the macroeconomic impacts of individual energy behavioral changes. In the absence of this integration, one should twist the CGE parameters and structure in an ad-hoc manner to permit some representation of a behavioral change. Instead, an ABM that relies strongly on the theoretical and empirical microfoundations from surveys, quantifies the patterns of behavioral change across heterogeneous households in a transparent way accounting for non-monetary aspects of individual energy choices.

Secondly, this article demonstrates that scaling up behavioral change dynamics has policy-relevant consequences at large scales. Our ABM grounded in theory and survey data quantifies the patterns of behavioral change, which could further be channeled into the CGE models that traces macroeconomic and cross-sectoral dynamics. Specifically, here we find that the regional dimension is important in a low-carbon economy transition driven by individual behavioral change. Some regions lag behind while others are pioneers, due to the heterogeneity in individuals' socio-demographics (e.g. education and age), structural characteristics (e.g. type and size of dwellings), behavioral and social traits, and spatial characteristics (e.g. urban vs. rural) which produce incremental differences at small scales. Yet, when aggregated, they cumulatively create disparities, which are amplified by macro-economic forces. Importantly, the inequality between regions decreases in the period of large investments (2015–2035) and starts to increase over time following it.

Finally, as behavioral barriers to climate change mitigation in designing policies gain attention, policy-makers would benefit from decision support tool that go beyond a stylized representation of households as perfectly-informed optimizers. Individual awareness, diversity in norms, and knowledge play a key role in a green economy transition and climate change mitigation policies should ideally combine the conventional macroeconomic analysis with these behavioral barriers and drivers. Considering bottom-up behavioral patterns would not easily change over time. To see substantial changes, we need a mix of external intervention, from soft information policies aimed to raise awareness bottom-up, to financial incentives altering the macro landscape of energy markets and technological transitions. At times, information and price-based policies create a non-linear effect on cumulative behavioral changes regarding energy use (Niamir et al., 2020b). Our approach demonstrates that with computational ABM directly linked to survey data and macroeconomic CGE models, individual behavioral heterogeneity and social influences can now be considered when designing implementable and politically feasible policy options.

The future work can go in two main directions: *advancing the modeling approach* and *improving the models dataset*. From the *modeling perspective*, future work could focus on introducing direct feedbacks between CGE-ABM, enabling the evaluation of price-based and information-policies jointly at multiple scales. The feedbacks between the two empirical models may be enabled through software wrappers and modern web interfaces for integration (Belete et al., 2019). In addition, due to the large number of parameters and multidimensionality of the generated data from any ABM (Lee et al., 2015), the global sensitivity and uncertainty analysis was out of scope of this article. Future work should focus on quantifying uncertainties that this integration of ABM and CGE models may impose, including for example exploratory analysis (Kwakkel and Pruyt, 2013) to understand the integrated model's behavior and its sensitivity to initial configurations of its parameters. From the *dataset perspective*, running surveys in more EU countries would improve the model accuracy, especially vital when predicting policy impacts. Also, data-wise, the behaviorally rich demand-side modeling could benefit from endogenizing 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.

Data availability

The extensive description of the models and data is presented in the Appendix of this manuscript. The *BENCH* model is calibrated based on the empirical dataset. We designed and conducted the survey in two provinces in Europe for the purpose of this research (Niamir et al., 2020a). The agent-based *BENCH* model is parameterized using the survey data on socio-demographic, economic, structural and behavioral attributes of households and their dwelling characteristic (Table A1.1). The *BENCH* agent-based model is open source and available on CoMSES (https://www.comses.net/).

The main database of EU-EMS model is the PBL-JRC world-wide MRIO database documented in https://ec.europa.eu/jrc/sites/jrcsh/files/jrc115439.pdf and available to download from https://data.overheid.nl/dataset/pbl-euregio-database-2000-2010. Besides this MRIO database we have also used the national accounts data from Eurostat (Research Project RPP 342/2016-CSIS-EU-SILC-HBS-LFS) and OECD for the construction of Social Accounting Matrices used to calibrate the model. According to the terms of use, authors are not allowed to redistribute the Eurostat micro-data. The derived intermediate result are available from the corresponding author upon reasonable request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the EU FP7 COMPLEX (Knowledge Based Climate Mitigation Systems for a Low Carbon Economy) Project No. 308601, the SCALAR European Research Council (ERC) Project, grant agreement No. 758014, and the IIASA-RITE distinguished young scientist award (recipient: Leila Niamir). We are thankful to Prof. Dr. Alexey Voinov (University of Technology Sydney, Australia) and Prof. Dr. Hans Bressers (University of Twente, the Netherlands) for their feedback and support. The authors would like to thank the TNS NIPO team for their collaboration in conducting the household survey. We also appreciate the participation of the survey respondents and the constructive feedback we received from the three anonymous reviewers.

Appendix 1. BENCH agent-based model

The *BENCH* ABM (Niamir et al., 2020b, 2018a) is developed to study shifts in residential energy use and corresponding emissions driven by behavioral changes among individuals.

Main processes of the model (ODD protocol)

Table A1.1
BENCH-v.3 ABM ODD protocol

Guiding Protocol		The BENCH-V.3 model
A. Overview	**A.1. Purpose**	The *BENCH-v.3* agent-based model is designed to study shifts in residential energy use and corresponding emissions at the regional level driven by behavioral changes among heterogeneous individuals. This empirically grounded model is of interest to (i) environmental scientists interested in modeling human behavior and economic institutions, (ii) energy economists working on micro aspects, (iii) scholars integrating individuals behavioral change in climate change mitigation modeling.
	A.2. Entities, state variables and scales	Agents (individuals) in *BENCH-v.3* model are heterogeneous in socio-demographic and dwelling characteristics, energy consumption and patterns, source of energy and energy provider, and behavioral factors. The *BENCH-v.3* simulations 1035 and 755 individual households in the Overijssel province, the Netherlands, and Navarre province, Spain over 34 years (2016–2050). One time step represents one round in the behavioral experiments. Each run consist of 34 time steps aligning to the 34 rounds in the behavioral experiments.
	A.3. Process overview	One time step represents one-year. In each time step a household goes through several processes: 1. Asses behavioral factors: - Knowledge activation - Motivation - Consideration 2. Calculate utilities 3. Pursue an action or not 4. Calculate saved energy and CO_2 emission 5. Social dynamics and learning process 6. Satisfaction and regret 7. Updates See Fig. 2 for algorithm and decision-making proccess in the *BENCH-v.3* agent-based model.
B. Design concept	**B.1 Theoretical and Empirical background**	In application to environmental- and energy-related choices, three behavioral change theories are commonly applied: theory of planned behavior (TPB), norm activation theory (NAT), and value–belief–norm (VBN) theory. - TPB, formulated by Ajzen (1980) 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). - NAT, originally developed by Schwartz (1977), operates in the context of altruistic and environmentally friendly behavior. It is mostly focused on anticipating pride in doing the "right" thing and on studying the evolution of feelings of guilt. - VBN theory (Stern et al., 1999; Stern, 2000) explains environmental behavior and "good intentions" such as willingness to change behavior (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).
	B.2. Individual decision making	We introduce a framework that combines the strengths of the three key behavioral theories, see Figure A1.1.
	B.3. Heterogeneity	Agents are heterogeneous in respect of the following variables, see Table A1.2: - Socio-demographic - Dwelling - Energy consumption - Energy provider - Behavioral factors
	B.4. Interactions, social dynamics and learning	Agents (heterogeneous individual households) engage in interactions and learn from each other. In particular, they can exchange information with neighbors, which may alter own knowledge, awareness, and motivation regarding energy-related behavior. We employ a simple opinion dynamics model (Acemoglu and Ozdaglar, 2011; Degroot, 1974; Hegselmann, 2002; Moussaïd et al., 2015) assuming that each agent interacts with a fixed set of nearby neighbors. The *BENCH_v.3* model is a spatially explicit model that takes the raster maps of the two NUTS2 regions as an input. Hence, an agent who is in active neighborhood where at least one out of eight nearest spatial neighbors within 1 raster cell (Moor neighborhood concept) undertakes an energy-related action will interact and exchange opinions. The idea of the Moore neighborhood comes from cellular automata literature and used only to enable opinion exchange between neighbors about climate and environmental awareness and compare norms. Agents compare values of their own behavioral factors – knowledge, awareness, and motivation – with those of their eight closest neighbors, and adjust their values for a closer match, see Fig. 3 and Eq. (3). However, the agents' heterogeneity beyond their spatial location (income, age, education) and economic factors affect individual choices of undertaking any of energy actions (I1–I3) or not.
	B.5. Spatial scale	Lowest scale: Individuals Highest scale: NUTS2 The focus of this research is on Overijssel, the Netherlands (NL21) and Navarre, Spain (ES22) NUTS2 regions, which consist of 25 and 10 main cities/municipalities respectively.
	B.6. Individual prediction	Individuals do not predict future condition.
	B.7. Stochasticity	There are various sources of stochasticity in the model: 1 Initial setting: Agents attributes (initialization are partly random) 2 During the process: Social dynamics and learning (process is partly random)
	B.8. Observation	

(*continued on next page*)

Table A1.1 (*continued*)

Guiding Protocol		The BENCH-V.3 model
		BENCH-v.3 estimates cumulative impacts of energy-related behavioral changes of individual households on electricity and gas consumption and CO_2 emissions. Reports: - Number of energy-related actions per year: investment, conservation, switching - Saved electricity and gas per action/year: investment, conservation, switching - Avoided CO_2 emission per action/year: investment, conservation, switching Across socioeconomic (age and education) groups (see Table 1) and cases (NL vs. ES).
	B.9. Implementation Details	The model is coded in Netlogo 6.0.4, Open source and available on CoMSES (https://www.comses.net) R is used for the result visualizations.
C. Details	**C.1. Initialization**	The variations in socio-demographic, dwelling and psychological factors among our survey respondents are used to initialize a population of heterogeneous agents in the *BENCH-v.3* model (see Table A1.1 and A1.3).
	C.2. Input data	The data on the behavioral and economic factors affecting household energy choices were collected using an online questionnaire (N = 1790 households) and serve as empirical micro-foundation of agent rules in the *BENCH-v.3* model.

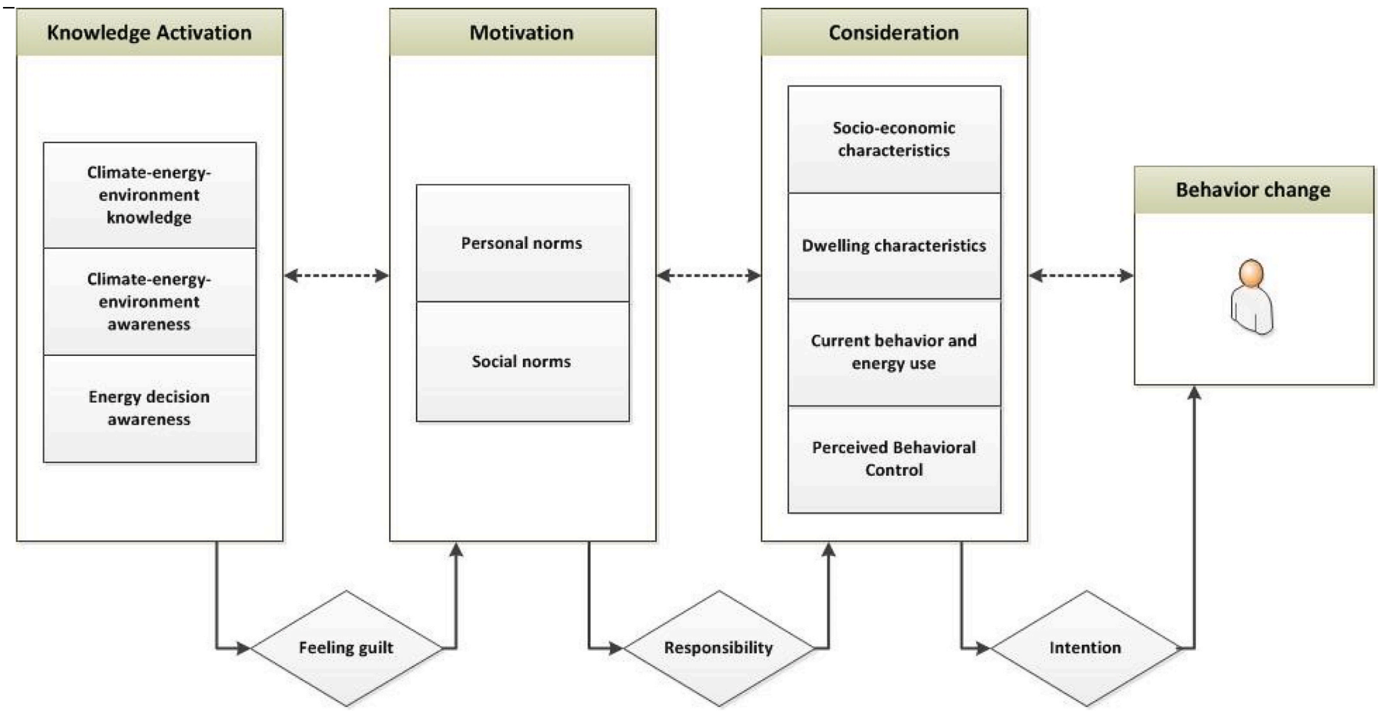


Fig. A1.1. BENCH-v.3 conceptual behavioral framework. Source: (Niamir et al., 2020a)

Table A1.2
Overview of main variables and parameters used in BENCH-v.3

Factors	Variables	Value range
Socio-demographic	Income	[1000–150,000]
	Education	[primary - doctoral]
Dwelling	Energy label	[a-f]
	Ownership status	[owner - renter]
Energy	Consumption	[500–5000]
	Provider	Grey, brown, green
	Energy saving habit	[0–3]
Behavioral	Knowledge	[1–7]
	Cee awareness	[1–7]
	Ed awareness	[1–7]
	Personal norms	[1–7]
	Social norms	[1–7]
	Intention a1	[1–7]
	Intention a2	[1–7]
	Intention a3	[1–7]

Data

The BENCH-v.3 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, 2019; Niamir et al., 2020a; Niamir and Filatova, 2017, 2016). The agent-based *BENCH-v.3* model is parameterized using the survey data on socio-demographic, economic, structural and behavioral attributes of households and their dwelling characteristic (Table A1.3).

Table A1.3
Survey data on households' characteristics and behavioral intentions. The data is used to parameterize households' behavior in the BENCH-v.3 ABM. Source: (Niamir et al., 2020a, 2018a)

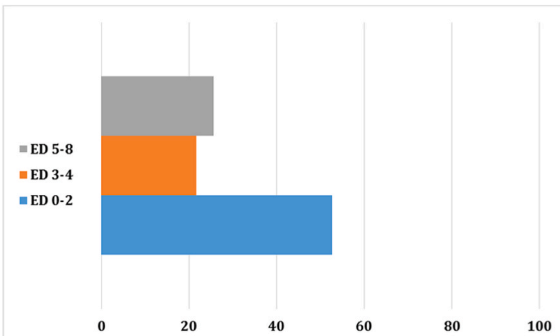
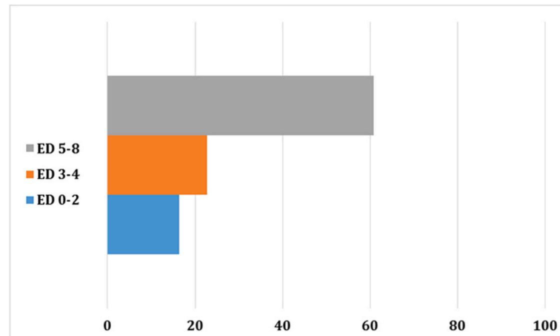
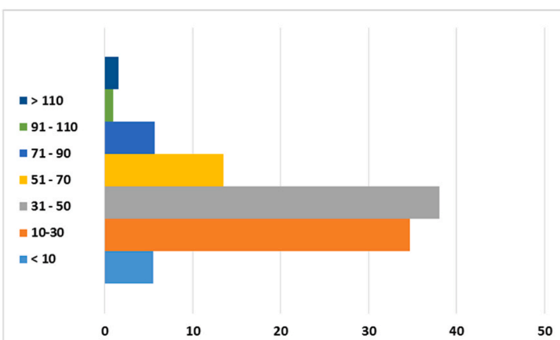
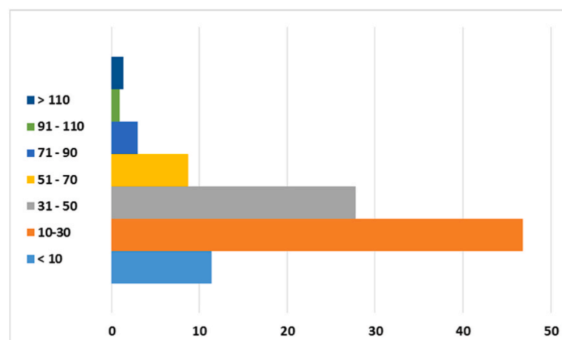
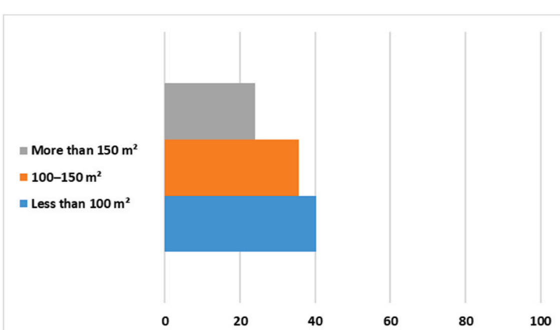
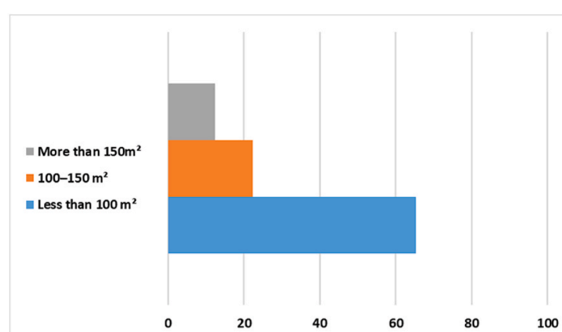
Factors	Overijssel	Navarre
Socio-demographic characteristics		
Gender	Female: 46.4% Male: 53.6%	Female: 57.1% Male: 42.9%
Age, years	53	41
Education, ISCED*		
Annual income, in thousand Euros per year		
Dwelling characteristics		
Type of residence	Apartment: 14.9% House: 85.1%	Apartment: 77.8% House: 22.2%
Tenure status	Owner: 71% Renter: 29%	Owner: 80.3% Renter: 19.7%
Size of residence		
Age of residence		

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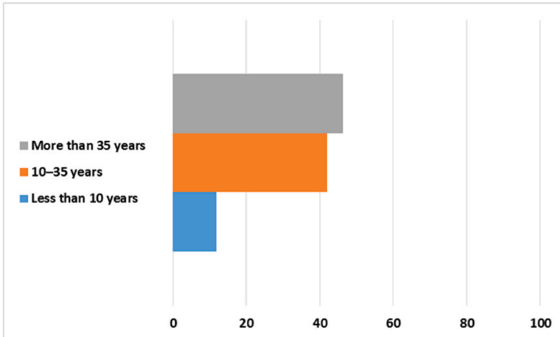
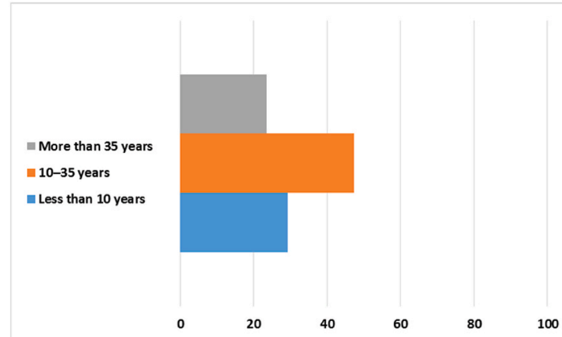
Table A1.3 (*continued*)

Factors	Overijssel	Navarre
		
Behavioral characteristics, value on the 1–7 scale		
Knowledge (*K*)	4.2 (0.7)	5.0 (0.8)
Awareness, Climate (A_C)	4.9 (0.8)	5.4 (0.8)
Awareness, Energy decision (A_E)	4.5 (1.0)	5.3 (1.1)
Personal Norms(N_P)	4.6 (0.9)	5.4 (1.0)
Social Norms (N_S)	3.3 (1.1)	4.5 (1.2)
Perceived Behavior Control (*PBC*)	4.4 (1.1)	5.0 (1.3)

* https://ec.europa.eu/eurostat/statistics-explained/index.php/International_Standard_Classification_of_Education_(ISCED).

Outputs

The agent-based *BENCH-v.3* model tracks the individual and cumulative impacts of three energy behavioral 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).

Appendix 2. Spatial EU-EMS CGE 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.[11] 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 analyzing 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

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 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 behavior by producers, average-cost pricing and household demands based on optimizing behavior. The CGE model database consists of tables of transaction values and elasticities: dimensionless parameters that capture behavioral 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 behavior of the whole population group or of the whole industrial sector as the behavior of one single aggregate agent. It is further assumed that the behavior of each such aggregate agent is driven by certain optimization criteria such as maximization of utility or minimization of costs. In following, detailed representation of the EU-EMS model and its main equations are presented.

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

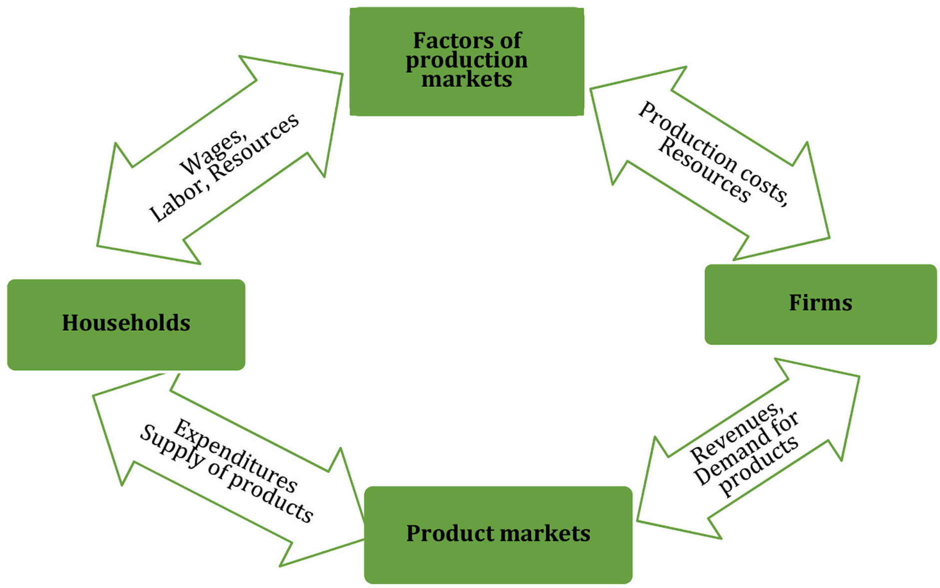


Fig. A2.1. Circular economic flow in the CGE EU-EMS model. Source: (Ivanova et al., 2019)

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 such as agriculture, whereas others specialize in modern sectors such as finance and industry. Those sectors are characterized by different levels of agglomeration and its importance. Traditional sectors do not experience any agglomeration effects, whereas modern sectors do; this allows some sectors to grow faster than other. The prototype model will incorporate the regional difference in sectoral specialization and hence the difference of agglomeration economies between the regions.

Table A2.1
Regions in EU-EMS CGE models. Source: (Ivanova et al., 2019)

Code	Name	Code	Name
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

(*continued on next page*)

Table A2.1 (*continued*)

Code	Name	Code	Name
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 maximization problem:()

$$U_r = \prod_i (C_{ri} - \mu_{ri})^{\gamma_{ri}} \tag{Eq. A2.1}$$

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:

$$C_{ri} = \mu_{ri} + \gamma_{ri} \cdot \frac{1}{P_{ri}} \cdot \left(I_r - \sum_j \mu_{rj} \cdot P_{rj} \right) \tag{Eq. A2.2}$$

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 a higher minimum level of consumption. The disposable income of the households consists of wages, return to capital and 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^D_{ri} 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 A2.2 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. The domestic production is generated according to nested production CES function, which is described by the following set of composite CES functions that follow the production structure from top to the bottom nest

$$X^D_{ri} = \left[(a_{ri} \cdot M_{ri})^{\rho_{M,KLE}} + ((1 - a_{ri}) \cdot KLE_{ri})^{\rho_{M,KLE}}\right]^{1/\rho_{M,KLE}} \tag{Eq. A2.3}$$

$$KLE_{ri} = \left[(b_{ri} \cdot E_{ri})^{\rho_{E,KL}} + ((1 - b_{ri}) \cdot KL_{ri})^{\rho_{E,KL}}\right]^{1/\rho_{M,KLE}} \tag{Eq. A2.4}$$

$$KL_{ri} = \left[(c_{ri} \cdot K_{ri})^{\rho_{K,L}} + ((1 - c_{ri}) \cdot L_{ri})^{\rho_{K,L}}\right]^{1/\rho_{K,L}} \tag{Eq. A2.5}$$

$$E_{ri} = \left[\left(d_{ri} \cdot E^{NELEC}_{ri}\right)^{\rho_E} + \left((1 - d_{ri}) \cdot E^{ELEC}_{ri}\right)^{\rho_E}\right]^{1/\rho_E} \tag{Eq. A2.6}$$

$$L_{ri} = \left[\sum_e \left(f_{rie} L^{ED}_{rie}\right)^{\rho_L}\right]^{1/\rho_L} \tag{Eq. A2.7}$$

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^{NELEC}_{ri} input of non-electric energy, E^{ELEC}_{ri} input of electric energy and L^{ED}_{rie} inputs of labor by type of education *e*.

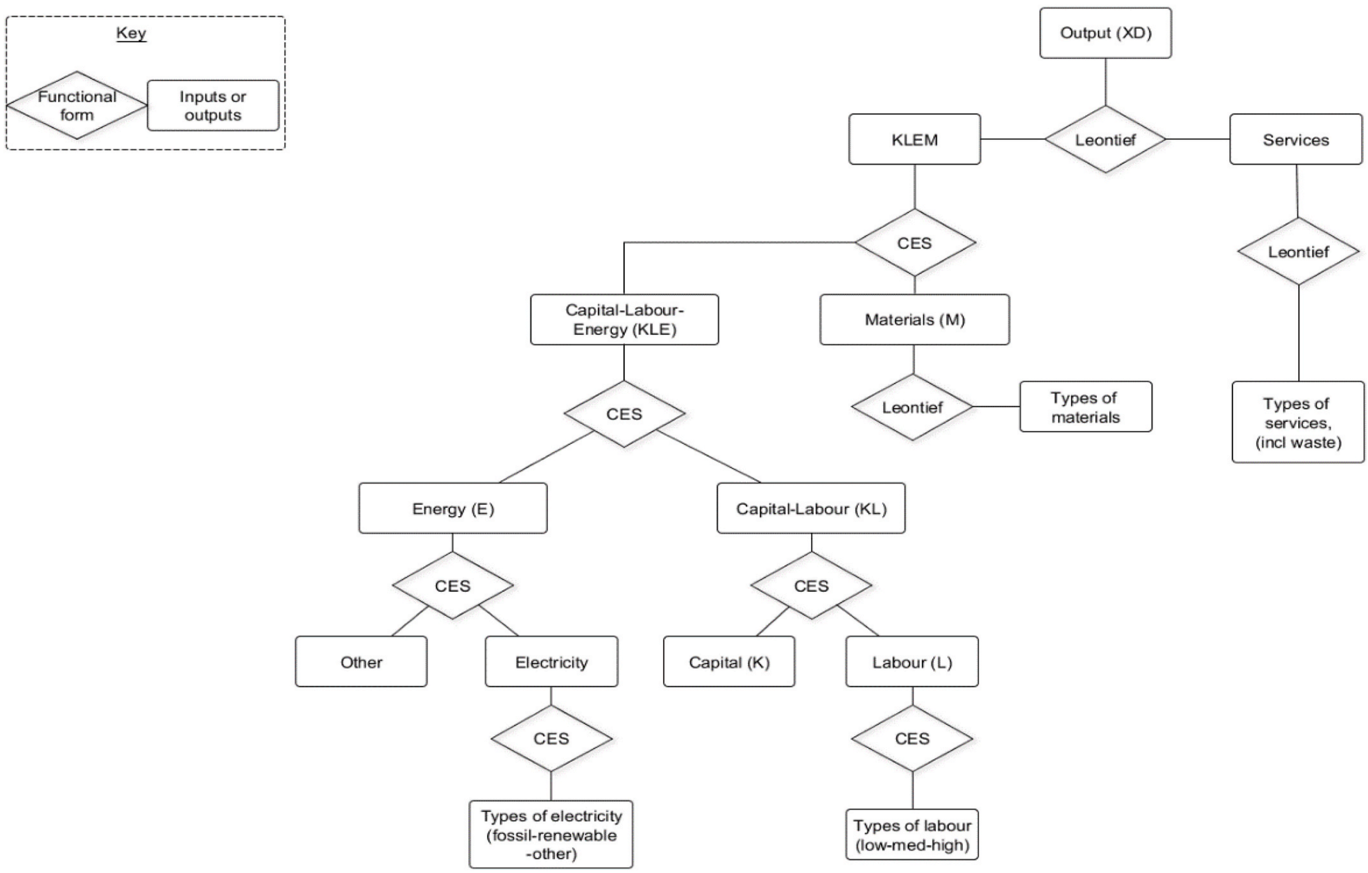


Fig. A2.2. Structure of KLEM production functions in the model. Source: (Ivanova et al., 2019)

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

$$X_{ri} = \left[\left(\alpha_{ri}^D \cdot X_{ri}^D\right)^{\rho_i} + \left(\alpha_{ri}^M \cdot X_{ri}^M\right)^{\rho_i}\right]^{1/\rho_i} \quad \text{(Eq. A2.8)}$$

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 the 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:

$$X_{ri}^M = \left[\sum_s \left(\alpha_{sri}^T X_{sri}^T\right)^{\rho_i^T}\right]^{1/\rho_i^T} \quad \text{(Eq. A2.9)}$$

Where α_{sri}^T is the calibrated share coefficient of the CES production function,X_{sri}^T is the flow of trade in commodity i from country $s$to country r. The coefficient $\rho_i^T = \frac{\sigma_i^T - 1}{\sigma_i^T}$ where σ_i^T 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 the 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 represents 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 nth 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

$$K_{tri} = K_{t-1ri}(1-\delta_i) + I_{tri} \tag{Eq. A2.10}$$

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 derived as a share of the total savings in the economy according to the discrete choice formula

$$I_{tri} = \frac{ST_{t-1r}B_{ri}K_{t-1ri}e^{\vartheta \cdot WKR_{t-1ri}}}{\sum_j B_{rj}K_{t-1rj}e^{\vartheta \cdot WKR_{t-1rj}}} \tag{Eq. A2.11}$$

$$WKR_{t-1ri} = \frac{r_{t-1ri}}{PI_{t-1r}} \cdot (g_r + \delta_{ri}) \tag{Eq. A2.12}$$

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 adjustment.

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

Appendix 3. Upscaling

Distance between countries is not only the geographical and therefore the regional economic integration should not happen regardless other local factors. Social structure, wealth and lifestyle, religion, institutional and economic conditions, and natural environment play a role in assessing cultural distance (Gobel et al., 2018; Hofstede, 2011, 2001; Kaasa et al., 2016; Schwartz, 2014; Vignoles et al., 2018). Table A3.1 summarized the value of cultural dimensions. In this study, due to the absence of more granular data, we use the Dutch case to approximate how the behavioral patterns may evolve in the North-West EU states, and the Spanish case for the South-East EU states, which is in line with the values presented below.

Table A3.1
Values of cultural dimensions for all EU countries, sources: (Čuhlová, 2018)

Country	PDI	INV
Austria	11	55
Belgium	65	75
Bulgaria	65	75
Croatia	73	33
Cyprus[a]	–	–
Czech Republic	57	58
Denmark	18	74
Estonia	40	60
Finland	33	63
France	68	71
Germany	35	67
Greece	60	35
Hungary	46	80
Ireland	28	70
Italy	50	76
Latvia	44	70

(continued on next page)

Table A3.1 (*continued*)

Country	PDI	INV
Lithuania	42	60
Luxembourg	40	60
Malta	56	59
Netherlands	38	80
Poland	68	60
Portugal	63	27
Romania	90	30
Slovakia	104	52
Slovenia	71	27
Spain	57	51
Sweden	31	71
UK	35	89

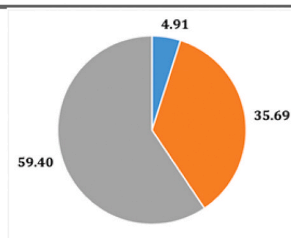
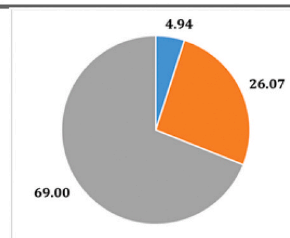
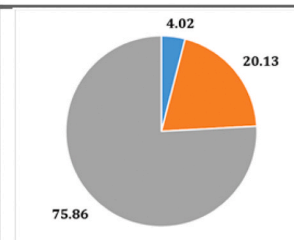
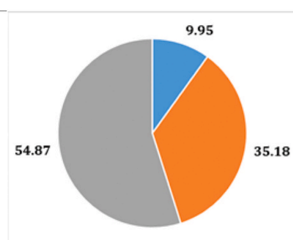
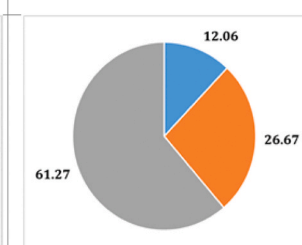
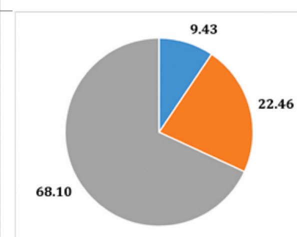
PDI – Power Distance Index, INV – Individualism.
[a] Complete data for Cyprus are not available.

Appendix 4. Results and discussions

Step 2: Scaling-up behavioral scenarios to national and EU level

Using the population projection scenarios for the EU28, we scale the dynamics in household energy behavioral changes in two provinces over time up to national and EU levels (Table A4.1).

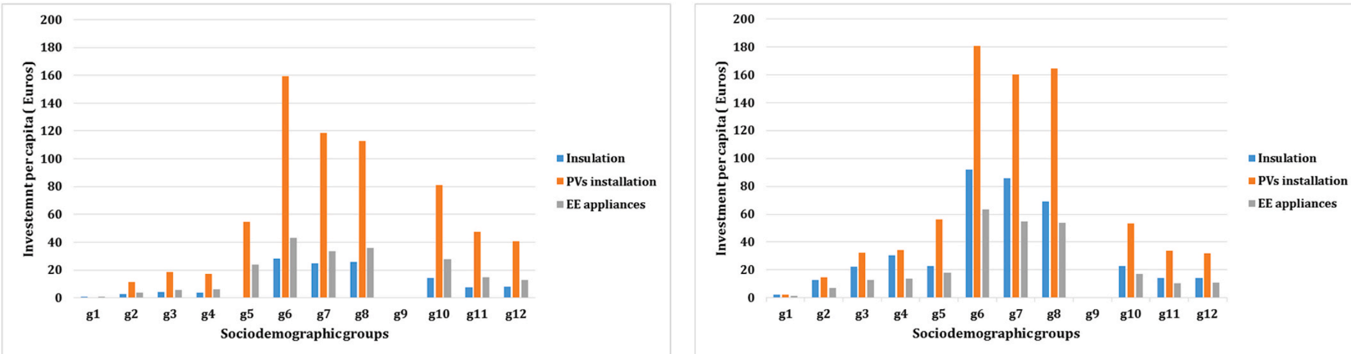
Table A4.1
Share of actions in two countries over time. Source: scaled-up BENCH-v.3 results.

		2020	2030	2050
The share of preferred actions (in percentage) Insulation PVs installation EE appliances	NL			
	ES			
Total number of actions	NL	3,291	22,026	50,322
	ES	1,546	29,894	123,545

Step 3: From regional to the national and EU28 economy

To estimate the macroeconomic and cross-sectoral impacts of individual energy behavioral changes, we link the up-scaled ABM output to the CGE *EU-EMS* model. The *BENCH-v.3* behavioral 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 analysis of EU-EMS results indicates that most of the EU28 regions benefit from the behavioral 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 behavioral changes since they save more electricity and gas.



(a) the Netherlands *(b) Spain*

Fig. A4.1. 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 A4.1). 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.

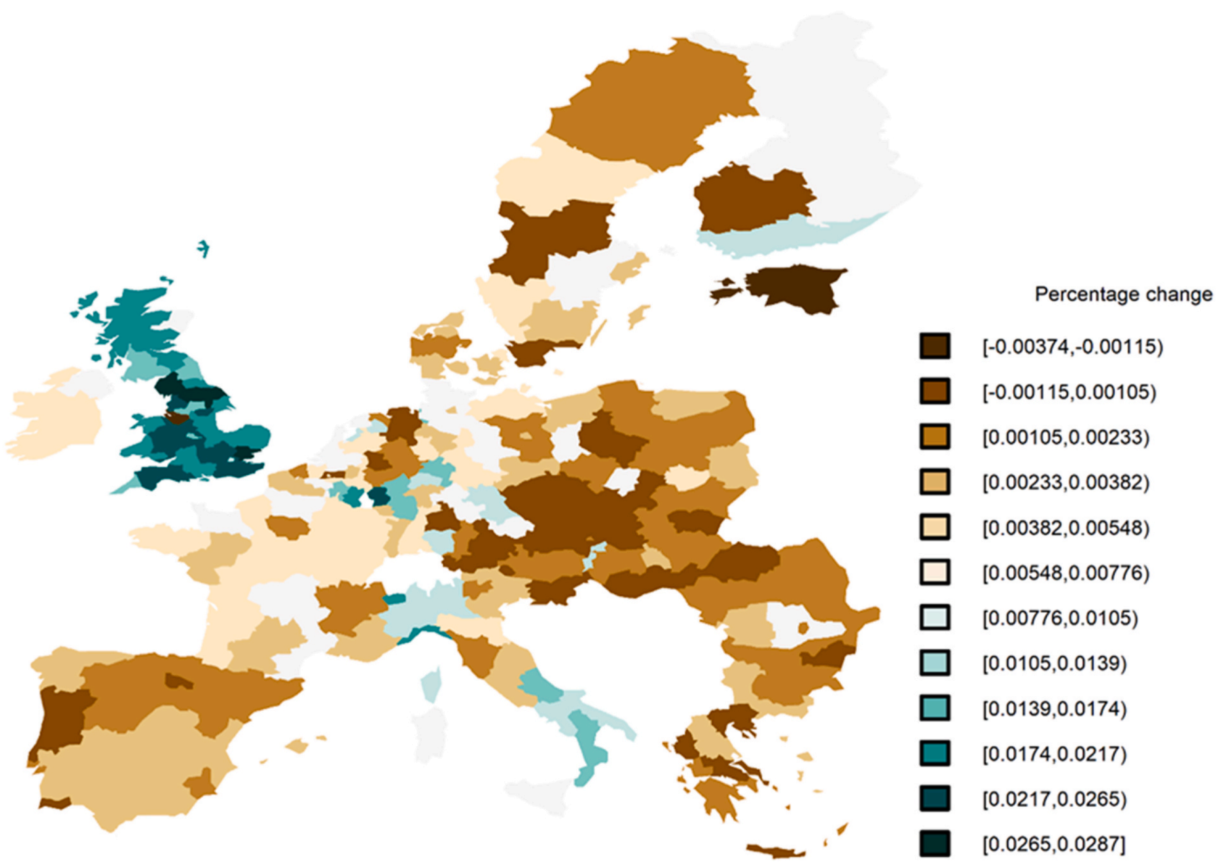


Fig. A4.2. Percentage changes in the levels of regional real GDP relative to the Baseline under the FD scenario in 2050 as an aggregated effect of households' behavioral changes, in millions of Euros. Source: EU-EMS and BENCH-v03.

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 behavioral scenarios on changes in the GDP and income. The changes in income presents similar patterns as changes in real GDP (see Fig. 6). However, it is interesting that different pattern in percentage changes in regional GDP levels from the absolute monetary changes in regional GDP is captured (see Figure A4.2). The majority of relatively large changes in GDP are located in Great Britain, Italy and Central Europe. This might be related to the assumed population and education level developments which influence the upscaling of the results of the *BENCH ABM* model.

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