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Original research article

Energizing building renovation: Unraveling the dynamic interplay of building stock evolution, individual behaviour, and social norms

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ABSTRACT

In recent years, discussions surrounding climate change have increasingly emphasized the significance of demand-side solutions. This shift has led to an interdisciplinary and bottom-up approach aimed at supporting global efforts to mitigate climate change. However, conventional modelling tools used to understand the energy demand system and to inform policymaking often fall short in capturing bottom-up dynamics accurately and at the required level of granularity. This is particularly evident in the nuanced and complex aspects of behavioural and social changes and their interactions. This research introduces a novel coupled -agent-based and integrated assessment modelling framework designed to analyse the advantages arising from diversity in renovation decisions, social dynamics, and the evolution of residential building stocks. This study demonstrates that, to effectively formulate realistic policies leading to substantial changes in building energy demand, policymakers require decision-support tools that extend beyond the confines of the rationality principle.

1. Introduction

While buildings are essential in providing shelter and services for people, they are also responsible for 21 % of global GHG emissions [1]. Studies show that demand-side mitigation strategies in buildings could technically reduce greenhouse gas (GHG) emissions by 78 % (6.8 GtCO2e) by 2050 [2] and make the transition to renewables much faster and more cost-effective [3]. Given the impact that household energy consumption has on emissions and an emerging shift in social norms, individual behavioural change becomes central in the discourse on climate change mitigation [2,4–8].

To assess the energy demand in buildings and its changes over time, we rely on models. So far, Integrated Assessment Models (IAMs) and macroeconomic Computable General Equilibrium (CGE) models have served as standard tools for quantitative policy assessments in climate change mitigation [9–13]. IAMs heavily focus on energy supply, technologies, investments and consumption patterns associated with GHG reduction policies by simulating markets for production and foreign exchange factors with equations that specify supply and demand behaviour. Carbon taxes, emission reduction targets, emission trading, renewable energy, and energy efficiency are the main policy levers addressed by sophisticated IAMs for energy policy assessments [11,14–16]. Yet, most IAMs assume a rational representative agent who makes optimal decisions under budget constraints, perfect information and competitive markets [17–19]. Their parameters can be either calibrated or econometrically estimated using time-series data. Therefore, IAMs are suitable for testing the economic effects of GHG reduction policies for short-horizons and near-term actions, making it challenging to integrate behavioural changes. Hence, their validity and capacity to provide unbiased climate mitigation policy advice is debated [6,17,18,20,21]. While IAMs have a strong focus on supply-side energy technologies [22,23], an improved representation of the end-use sectors is needed to capture the full potential of demand-side solutions.

IAMs typically consider the building sector with a lower level of detail, neglecting the building infrastructure [24,25] and requiring further linkage with future demand for buildings [26]. In recent developments, IAMs were coupled to sectoral building end-use models to account for infrastructure and stock dynamics and improve the representation of demand-side decarbonisation strategies [24,27–29]. Despite improving socio-economical and technological detail, these coupled models consider behavioural aspects in a simplified way and often with exogenous assumptions, e.g. on building floorspace and activity levels. However, in reality, individuals make decisions shaped by their diverse preferences, socio-economic conditions, behavioural and lifestyle biases, climate-energy literacy, social peer influence, and technology and infrastructure availability. Each of these factors provides

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its own policy entry point for demand-side mitigation. Individual energy decisions -for example, investment in building renovation- especially when amplified through social context (interaction and learning), shape energy demand. Individuals can play an essential role in net-zero emissions transition by changing their behaviours. Broader engagement of behavioural and social sciences is needed to identify promising opportunities for a low-carbon society [2,30–33]. Thus, a new generation of models is needed to reflect these complex decision environments [18].

Agent-based Modelling (ABM) is considered the most promising approach to address the complexity of individual decisions in energy-climate models [6,18,34]. This method is a frontrunner as it is designed to account for different behaviours, bounded rationality and social influences. Several behavioural ABMs in the buildings sector are developed and grounded in empirical data [34–36], yet the focused area, spatial operation, and their feedback on the structural and physical aspects remain limited. Consequently, this prevents assessing economy-wide impacts realistically and generalising ABMs' results.

In this study, we introduce an innovative modelling framework that combines ABM and IAM to address the limitations associated with each approach. This marks the initial step towards the integration of ABM and IAM by enhancing the modelling of a particular sector, namely, buildings, as an integral module within an IAM. Linking IAM with micro-level behaviourally-rich ABM can operationalise behavioural and social changes in formal policy analysis and open new synergies between socio-behavioural, infrastructural and institutional approaches.

Earlier attempts to integrate ABM with IAM/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, the authors leave it at the conceptual level without an implementation. Niamir et al. (2020) present a method of systematic upscaling of individual heterogeneity and social dynamics to combine ABM and CGE models. However, many studies comprehensively reviewed IAMs and ABMs, highlighted their strengths and weaknesses and emphasized the models integration as one way forward [37,38]. To the best of our knowledge, there is no empirical example of resolving the key methodological differences between ABM and IAM modelling while aligning with survey data on behavioural heterogeneity. We believe this is a unique model complementary exercise which accommodates heterogeneity, adaptive behaviour and interactions, bounded rationality and imperfect information.

This paper closes the gap between what the current energy modelling can do and what social science highlights as pro-environmental behaviour in the transition to low energy demand. To do so, we present a systematic way to bring empirically-based heterogeneous households' energy decisions and social influences to behavioural and social modelling (ABM) coupled with the buildings module of the energy model (IAM). Our choice to emphasize the buildings module within the IAM is primarily driven by our aim to align with the scope of our ABM domain. This, in turn, establishes the initial point of interaction with the broader IAM framework.

2. Methods

This research presents a novel model coupling framework to capture energy-climate benefits of residential energy behavioural changes and social interactions, considering renovation decisions while accounting for the building stock evolution. The framework consists of two main interlinked models: a bottom-up energy behavioural agent-based model (BENCH); and a bottom-up building stock energy model (MESSAGEix-Buildings) part of an IAM.

2.1. Bottom-up modelling

2.1.1. BENCH agent-based model

Originally, the BENCH ABM [6,36] was developed to investigate the role of behavioural changes with respect to 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. ownership status, type, size, age), energy consumption patterns (e.g. electricity and gas consumption, energy provider), and behavioural factors (e.g. awareness, personal norms, social norms). BENCH is spatially explicit, with behavioural rules of agents calibrated based on the survey data for two EU provinces: Navarre, Spain and Overijssel, The Netherlands [33]. The BENCH model integrates both the elements of a rational choice (e.g. economic and financial) as well as contextual behavioural factors. BENCH is capable of accurately capturing the diversity within renovation actions. Heterogeneous households engage in interactions and learn from each other. In particular, they can exchange information within their social networks (e.g. family, neighbourhood, and institutions), which may alter their own awareness and motivation regarding adaptation. We advance this ABM further to permit integration with the MESSAGEix-Buildings both in terms of the theoretical consistency of functional forms used in ABM and IAMs, as well as the datasets and scenario assumptions. In particular, BENCH (version 04) focuses on a household decision on building renovation.

2.1.2. MESSAGEix-Buildings

MESSAGEix-Buildings [28] is a bottom-up modelling framework to assess the evolution of large building stocks and related energy demand under different socio-economic, technology, climate and policy scenarios soft-linked to the IAM MESSAGEix [39]. MESSAGEix-Buildings brought several advancements in the representation of the buildings sector in IAM, by explicitly accounting for housing and households heterogeneity, building stock turnover, and key activities and energy efficiency improvements dynamics. This allowed for overcoming the simplified approaches for sector energy demand projections commonly used in IAMs, often GDP-driven and limited in considering sectoral transformations and policies. In this study, we focus on the residential sector and use two main sub-modules in MESSAGEix-Buildings: CHILLED (Cooling and Heating gLobaL Energy Demand model), an energy demand model for space heating and cooling based on spatially explicit variable degree days calculation; and STURM (Stock TURnover Model of global buildings), a stock turnover model based on dynamic material flow analysis (MFA) to assess new constructions, demolitions and renovations. The scope and resolution of the model are flexible both in space and time, with typical scope ranging from national to global and mid- to long-term assessments. Here, we run the model for Spain and the Netherlands, operating at the national level, with five-year timesteps. MESSAGEix-Buildings has high granularity in representing heterogeneous households and housing characteristics. In this study, we differentiate the characteristics and energy demand of the housing stock according to the following dimensions: location (urban and rural), climatic zone, housing types (single-family and multi-family), periods of construction and energy efficiency levels (existing built before 1945, between 1946 and 1990, and between 1991 and 2015, renovated, and newly constructed after 2015) and energy carriers for space heating (biomass, coal, natural gas, oil, district heating and electricity). Adding more granularity, e.g. via additional segmentation of periods of construction, could support further analysis of the heterogeneities in the stock, but results in additional model complexity and computational burdens, that will be addressed in future model implementations. While MESSAGEix-Buildings can endogenously represent energy efficiency investment decisions of households via dedicated discrete choice models [28], in this study we use fixed renovation rates when running the model stand-alone.

Granularity and heterogeneity in both models data is presented in the Supplementary Information (Tables SI.1–3).

2.2. Integration framework

An overview of the coupling modelling framework is provided in Fig. 1. The workflow consists of three main steps: 1) the building stock turnover and future configuration is assessed in MESSAGEix-Buildings; 2) the building stock configuration is passed over to BENCH and renovation decisions are estimated accounting for heterogeneity in household socio-economics and dwelling characteristics; 3) renovation actions are passed over to MESSAGEix-Buildings and updated building stock configuration and energy demand are calculated.

2.2.1. Step1. Preparatory stock turnover (MESSAGEix-Buildings)

In the first step, we run the STURM model to assess the housing stock turnover in future years and report new constructions and demolitions in terms of both housing units and floorspace. Demolitions are calculated by applying housing type-specific probabilistic demolition curves to the different vintage cohorts. New constructions are determined based on population driven demand for housing units, accounting for replacement of demolished units. Based on demolitions and new constructions, we obtain an updated configuration of the housing stock at every timestep (please, refer to [28] for more details). In this step we don't consider renovations and implicitly assume that the building lifetimes are dependent on housing types but not on energy renovations. While there are often linkages between *energy* renovations to improve buildings' energy efficiency and *structural* renovations to enhance building structural performance and extend buildings' lifetime, the relationship between the two is mostly unclear due to data scarcity. Here, we focus on *energy* renovations only and assume the continuation of current trends in building demolitions. The stock time-series and share of housing by vintage is passed over to BENCH ABM. Initially, the BENCH ABM does not incorporate any estimations or narratives related to demolishing and new construction. Essentially, in this initial iteration, households' dwelling arrangements remain static, with the model only tracking the age of the buildings.

2.2.2. Step2. Households energy renovation decisions (BENCH)

In BENCH ABM, household agents are heterogeneous in socio-economic and dwelling characteristics, preferences, and awareness of the environment and climate change, so they can pursue various energy-related choices and actions. Namely, they vary in six economic attributes: (1) annual income in euro; (2) annual electricity consumption in kWh; (3) dwelling tenure status—owner or renter; (4) energy label of their dwelling varying from A to F; (5) the age of their dwelling; and (6) the size of their dwelling in m2. Data for all these variables come from the survey [33]. The annual growth value of socio-economic variables representing households' income and electricity consumption (in 5 quintiles) comes from the EXIOMOD computable general equilibrium (CGE) model [40].

The behavioural and social aspects impacting households' energy decisions also vary among agents and include (1) general knowledge about the environment and climate changes; (2) awareness of the consequences of their actions and behaviour (with a focus on energy renovation); (3) information regarding energy investments and renovation; (4) personal norms, which are values that people hold, e.g., feeling good when they are energy-efficient; (5) subjective norms, which are perceived social pressure on whether to engage in a specific behaviour motivated by observing energy-related actions of neighbours, family, and friends; (6) perceived behavioural control, which refers to the household perception of the ease or difficulty of performing the building renovation. These behavioural and social variables are updated over time (annually) through social dynamics and learning procedures (see [6] for more details). Agents' decision processes closely follow the conceptual framework (Fig. 2) behind the household survey.

In accordance with the Theory of Planned Behaviour and Norm Activation Theory from psychology [41,42], we assume that boundedly rational individuals in BENCH make decisions following a number of cognitive steps: knowledge activation, motivation, and consideration [6,19]. Fig. 2 shows heterogeneous households in socio-demographic characteristics (e.g. age, education, income), behavioural and social factors (e.g. attitude, personal norms, subjective norms), dwelling conditions (e.g. type, size, energy label), and electricity and gas consumption follow a cognitive process to decide whether to pursue investment in buildings insulation and renovation. Niamir et al. (2018a) describe how each individual's knowledge activation and motivation are

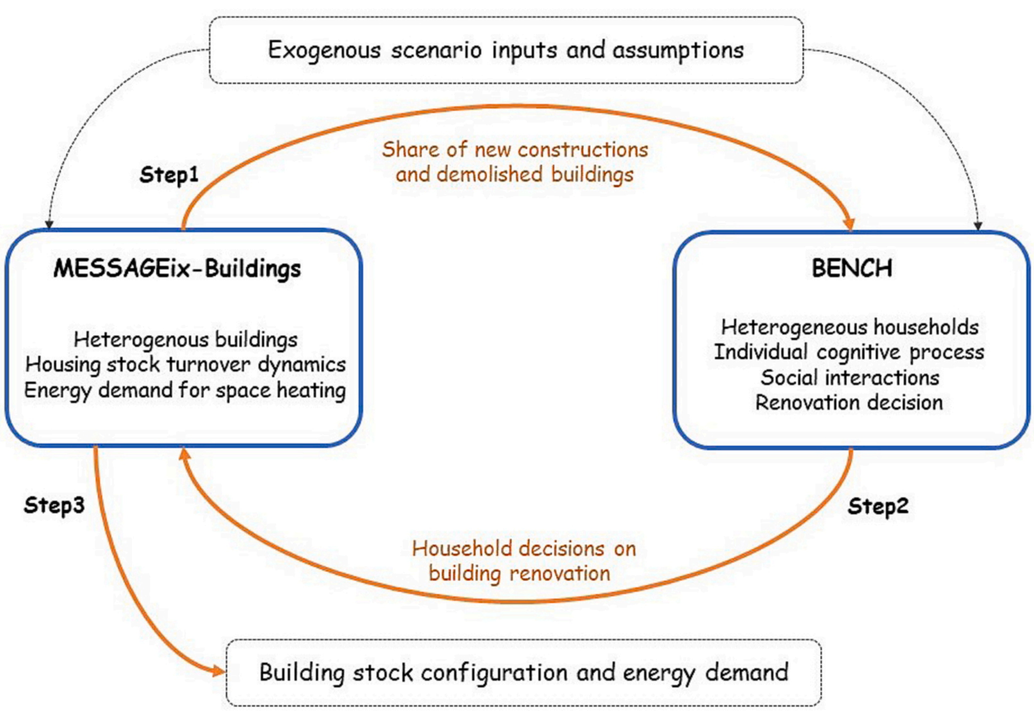

Fig. 1. Models coupling framework.

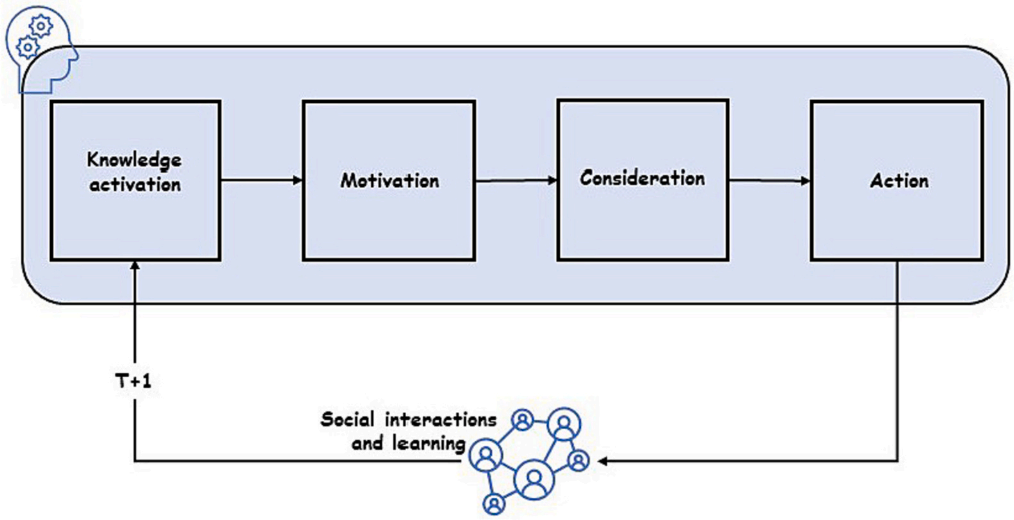

Fig. 2. A household decision-making process in the BENCH ABM.

measured and calculated at the model initialisation stage based on the survey data.

Applying BENCH ABM sheds light on the effects of heterogeneous household renovation decisions and explores the impact of socio-economic, behavioural heterogeneity and social dynamics in the two European countries, The Netherlands and Spain, over 33 years (2017–2050). As a result, the aggregated share of heterogeneous households who took the renovation decision is reported based on three main buildings age categories: new buildings (<10 years), middle age buildings (11–35 years), and old buildings (>35 years). We provide detailed mapping between the age of buildings in BENCH, that is moving over time, and the three periods of construction in MESSAGEix-Buildings, to ensure full consistency between the two models.

2.2.3. Step3. Building stock turnover and energy renovation

Finally, we re-run the scenarios in the STURM building stock turnover model incorporating the renovation decisions assessed in BENCH and generate new time-series of the housing stock configuration, as a result of the demolitions, new constructions and renovations calculations in the stock turnover model. Renovations are provided as share of renovated buildings by the vintage cohort. Types of renovations and estimation of corresponding energy savings are parametrized consistently with the BENCH model setup for the scenario runs (see Section 2.3). Energy intensity for space heating is calculated for a set of building archetypes representing different housing cohorts using the CHILLED module. The calculation is based on variable degree days (VDD) applied to a spatial grid with 0.5° spatial resolution, population-weighted, and aggregated at the level of countries and climatic zones. VDD are calculated for each month (m) with the following equation:

$$VDD_{h,m} = \sum_{d=1}^{dm} \left(T_{bal,m} - \overline{T}_{out,d}\right)^{+}$$

where dm is the number of days (d) in the given month, $T_{bal,m}$ is the monthly balance temperature, where nor heating nor cooling is necessary, $T_{out,d}$ the average daily temperature.

The VDD method accounts for building characteristics and occupants' behaviour in the calculation of heating demand by analytically calculating the balance temperature. Annual final energy for space heating is finally calculated aggregating results from the monthly calculation and accounting for the conversion efficiency of the heating system. (see [28] for more details).

The total final energy demand for space heating is finally calculated by combining a) the floorspace projections for different housing cohorts by period of construction and energy efficiency level from the STURM module and b) the energy intensity per unit floorspace of the different housing cohorts calculated by country and climatic zone with the CHILLED module. A detailed list of the input data used for the calculations is reported in the supplementary information.

2.3. Scenarios and model runs

2.3.1. Step1. Buildings stock turnover scenario

The building stock evolution and energy demands in MESSAGEix-Buildings follow a baseline (B) consistent with the Shared Socio-economic Pathway SSP2 [43] and represent the continuation of historical patterns. SSP2 has medium challenges to both mitigation and adaptation [44]. In the residential sector, the baseline is characterized by a continuation of current trends in housing size growth, moderate energy efficiency increases, and medium energy demand levels [28].

2.3.2. Step2. Behavioural and social scenarios

Besides being heterogeneous in terms of socio-demographic 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 ABM exhibit heterogeneous behavioural characteristics, such as knowledge and awareness, engaging in social interactions and learning. BENCH_v04 ABM introduces two end-user behavioural scenarios (Slow and Informative Dynamic) by differentiating between the intensity of social interactions and the learning speed (see Table 1). While the Slow Dynamic (SD) scenario represents the BENCH ABM baseline, where social interactions of heterogeneous households are limited, the Informative Dynamic (ID) scenario assumes an intense information policy that activates and promotes building renovation through raising knowledge and motivation across the entire population.

2.3.3. Step3. Building stock turnover and energy renovation

We combine the building stock evolution Baseline (B) in MESSAGEix-Buildings with the two end-user behavioural scenarios (Slow Dynamic (SD) and Informative Dynamic (ID)) from BENCH ABM to investigate the building stock evolution and renovation actions under different social dynamics and effects on energy demand for space heating. The two resulting scenarios (B-SD, B-ID) are compared against two benchmark scenarios (without social dynamics) run in MESSAGEix-Buildings and assuming a fixed renovation rate over time. In the first benchmark scenario (Benchmark with Low Renovation rate (B-LR)), the current renovation rates (1.05 %/yr in Spain and 0.95 %/yr in the

Table 1
Scenario setting, buildings stock and behavioural and social scenarios.

Scenarios	Type	Setups/explanation
MESSAGEix-Buildings (Step1)		
B (Baseline)	Buildings stock	Continuation of current building trends (SSP2)
BENCH (Step2)		
SD (Slow Dynamic)	behavioural and social	Slow: in an active neighbourhood: individuals interact with four available neighbours
ID (Informative Dynamic)	behavioural and social	Informative: in an active neighbourhood: individuals interact with all available neighbours + Intense information policy
Combined BENCH and MESSAGEix-Buildings (Step3)		
B-SD	Buildings stock + Behavioural and social	Building stock turnover + Slow behavioural and social dynamics
B-ID	Buildings stock + Behavioural and social	Building stock turnover + Informative behavioural and social dynamics
MESSAGEix-Buildings (Benchmark scenarios)		
B-LR (Benchmark: low renovation rate)	Building stock	Building stock turnover + Low fixed renovation rate
B-HR (Benchmark: high renovation rate)	Building stock	Building stock turnover + High fixed renovation rate

Netherlands) are kept constant until 2050, representing the continuation of current practice. The second benchmark scenario (Benchmark with How Renovation rate (B-HR)) assumes a doubling of the renovation rate in line with the European "Renovation Wave" ambition [45]. In the B-HR scenario, renovation rates accelerate to 2.5 %/yr by 2025 and remain constant until 2050. In agreement with similar scenarios from other studies [46], we assume that 20 % of the renovations are deep (reaching 60 % energy reduction) and the rest medium and shallow (average 30 % energy reduction) to reflect prevailing renovation practices and align with the BENCH model setup.

3. Results and discussion

In the following, we present and discuss the results of each integration step.

3.1. Step1. Building stock turnover (MESSAGEix-Buildings)

Fig. 3 shows the projections of residential floorspace, construction and demolition rates for Spain and the Netherlands in the Baseline (B) scenario calculated in MESSAGEix-Buildings. Total floor space slightly increases in Spain and stays mostly constant in the Netherlands, as a result of slow population growth and minor changes in housing size until 2050. Construction rates are not significantly changing from the current values (up to 1 %/yr), while demolition rates are only slightly increasing. As a result of these dynamics, the composition of building vintage cohorts only partially shifts over time. A large part of the housing stock (45–55 %) is represented by buildings older than 35 years, and therefore less energy efficient, in both countries. Newer buildings (vintage <10 year) constitute only around 20 to 30 % of the total housing stock, and the share is decreasing over time as a consequence of construction rates slowing down (see Fig. 4). The time-series of housing stock composition are passed over to the BENCH ABM model to account for infrastructure vintage in renovation decisions of households.

3.2. Step2. Households renovation decision (BENCH)

In this step, we run the *BENCH ABM* for Spain and The Netherlands under the two behavioural and social scenarios (SD and ID) to track heterogeneous household renovation decisions capturing non-linearities in renovation rate over time and space. Given the stochastic nature of ABMs, we run *BENCH ABM* multiple times under the same parameter settings for each scenario. The ABM results presented below plot the means across 100 random runs.

In scenario SD (as *BENCH* baseline), the heterogonous households with various income, age, education, energy consumption, personal and social characteristics, preferences and building conditions go through the process to decide whether to apply renovation and save energy or not (see Section 2.2.2). Fig. 5 shows that introducing heterogeneity to the household's economic, behavioural, social and building attributes leads to non-linear trends of renovation investment over time in Spain and the Netherlands. The results show Dutch households -up to 9.4 % in the old buildings- intend to invest in renovation and save energy rather than those in Spain.

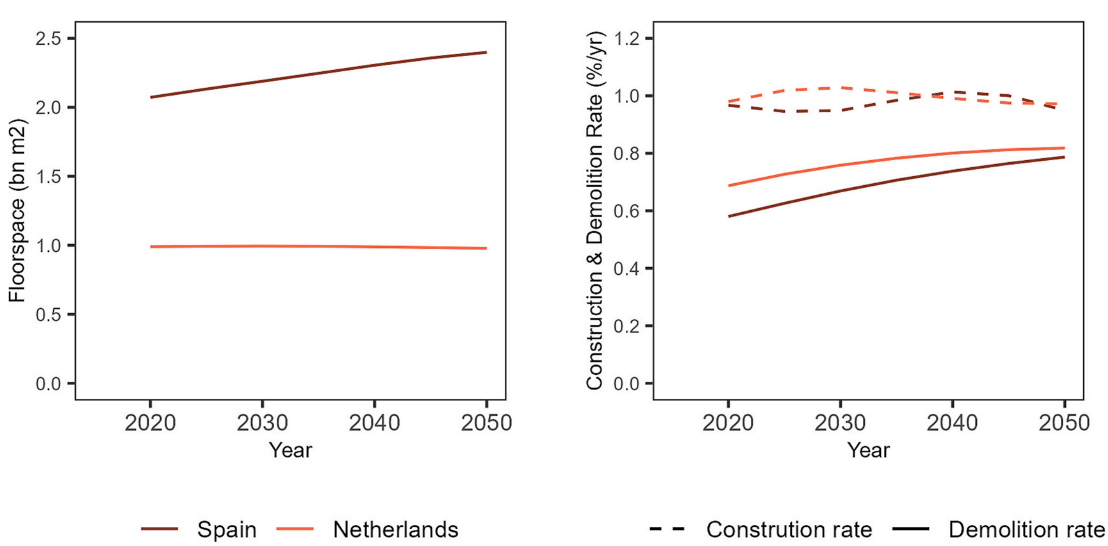

Fig. 3. Projections of total residential floorspace (left panel) and average construction and demolition rates (right panel) for Spain and the Netherlands in the Baseline (B) scenario.

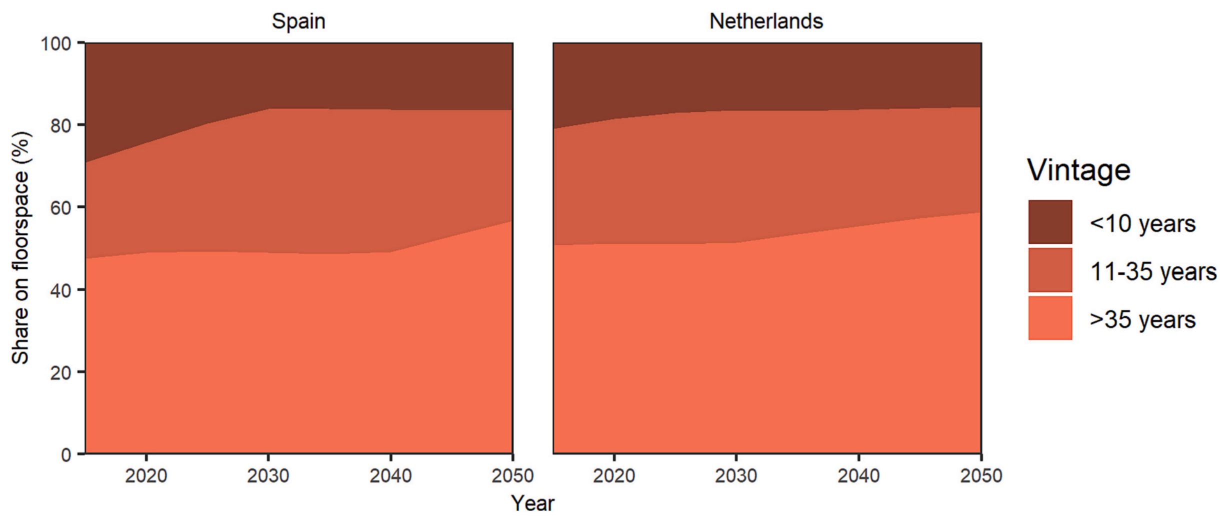

Fig. 4. Composition of the housing stock over time by vintage categories for Spain and the Netherlands in the Baseline (B) scenario.

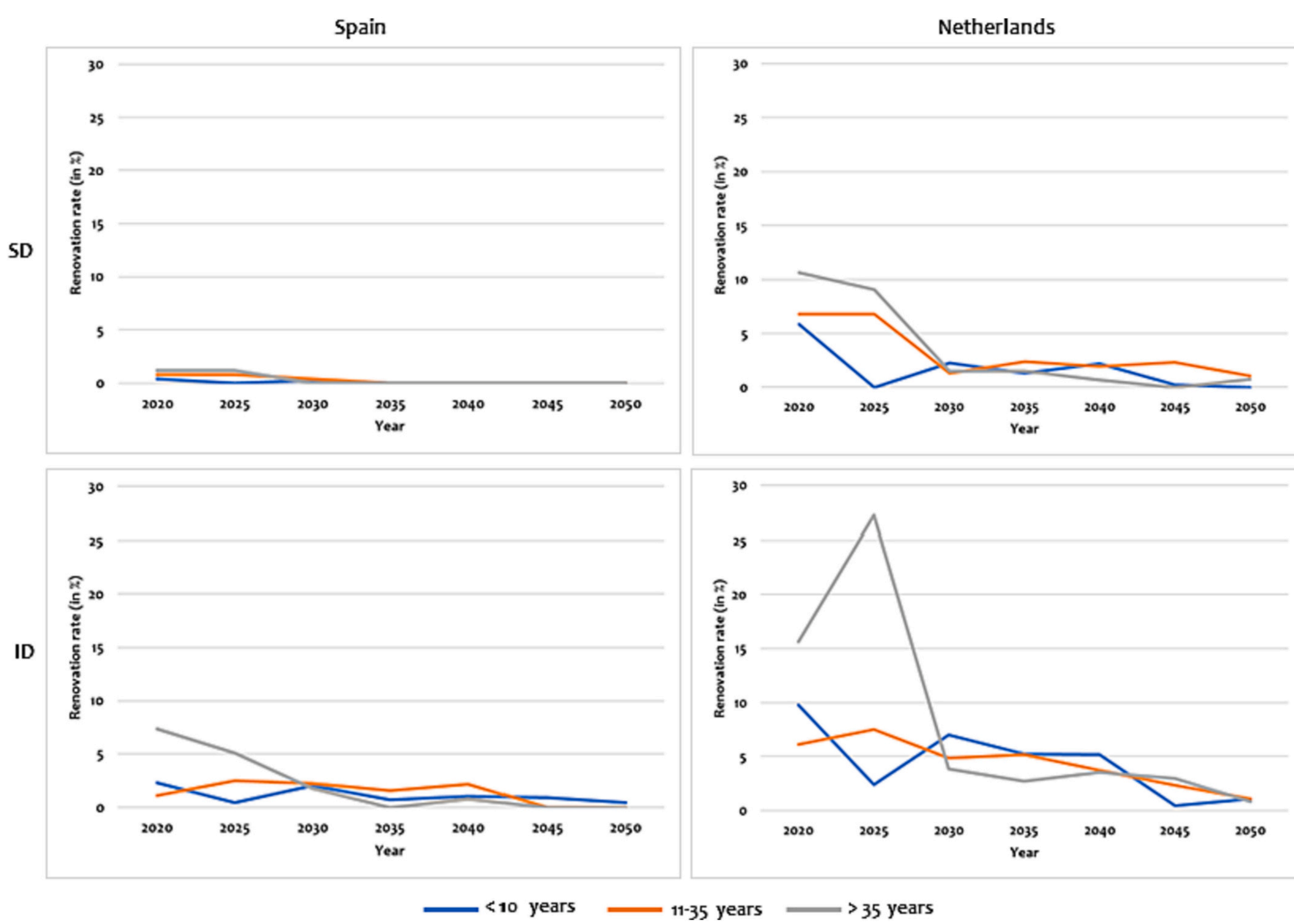

Fig. 5. Heterogeneous household renovation decision over time by vintage categories in Spain and the Netherlands under SD and ID scenarios. The renovation rate (%) is presented as the percentage of households renovation within specific age cohorts (<10, 11–35, >35), relative to the total number of households in each cohort, observed over a 5-year period.

Scenario ID shows what happens if we have more intense social dynamics within a neighbourhood – therefore, the diffusion of information is faster inside society. In other words, this stimulates the soft policy pressure where households receive enough knowledge on energy consumption and information on renovation strategies and costs. We observe the impact of fast social interaction alone, activates households and delivers an additional 4 % and 18.2 % share of renovation in Spain and the Netherlands, respectively. As Fig. 5 shows, under scenario ID, not only more households decide to invest in renovation in the early years (between 2020 and 2030), but also information diffusion activates other households in the years after. In addition, our results show that the main barriers in the renovation decisions in both cases, particularly between 2030 and 2050, are rooted in 1) ownership status -households who rent the building are not allowed to change the building structure; and 2) renovation affordability -the majority of household, particularly in the case of Spain- who are the owner and motivated enough to invest on building renovation, cannot afford the costs.

Fig. 6 presents what happens in the presence and absence of buildings' stock turnover dynamics. This highlights how buildings' age and structural changes,– such as new construction and demolishing old buildings, introduce a dynamic element into household renovation decisions. This dynamic primarily arises from the fact that renovation decisions are significantly influenced by the age of the building, a finding that aligns with our empirical study [33]. In other words, the age of the building plays a pivotal role in shaping household renovation choices. Fig. 7 illustrates that behavioural and social incentives activate households to invest in building renovation over various income groups. Two distinct scenarios are depicted: 1) the SD scenario, supported by empirical research, underscores that the middle and high-middle income groups exhibit a higher level of activity in pursuing renovation initiatives; 2) the ID scenario illustrates that social dynamics play a pivotal role in influencing household decisions related to renovation, a trend evident across all income categories. While we observe a more pronounced impact, up to approximately 9 %, on the middle to high-income groups over time, the renovation rate in low and low-middle-income groups has increased by around 5 %. This suggests that we have a greater potential to engage and activate higher-income households through information dissemination and awareness. However, lower-income households may also become motivated and express an intention to renovate when provided with information. Yet, they may encounter additional obstacles, such as budget constraints or residing in rented buildings, which hinder their ability to undertake renovation projects. As an example, when comparing SD and ID, it is evident that the renovation rate for the high-income group increased by >6 % in 2030.

3.3. Step3. Buildings stock turnover and energy renovation

In the last step, we run the MESSAGEix-Buildings model combined with renovation inputs from BENCH to simultaneously account for socio-behavioural and building stock dynamics. Fig. 8 shows the average yearly renovation rates for the entire housing stocks of Spain and the Netherlands over time for different scenarios. Renovation rates are higher in the B-ID scenario, under more intense social dynamics, and lower in the B-SD scenario. In particular, for the Netherlands, renovation rates accelerate in the initial period and then slow down over time as upgrading of the existing housing stock advances. In Spain, renovation rates are relatively lower due to higher barriers towards energy efficiency interventions. Renovation rates for the B-SD and B-ID scenarios can be compared with the additional scenarios B-LR and B-HR with fixed renovation rates, showing more complex dynamics over time that cannot be capture by exogenously projected renovation rate.

Different renovation rate influence the composition of the housing stock by different energy efficiency cohorts over time (Fig. 9). The share of renovated buildings by 2050 is higher in the B-ID scenario for both Spain and the Netherlands under faster upgrading of existing buildings. It is possible to notice that, due to slow building cycles, the existing housing stock will still constitute between 60 and 70 % of the total housing stock in 2050 in the two countries. Thus, renovation plays a key role in reducing future buildings energy demands.

Projections of final energy demand for space heating in different scenarios are reported in Fig. 10. Final energy is lower in the B-ID scenario for both Spain and the Netherlands as a result of higher renovation rates. Energy demand reductions for space heating are more substantial in the Netherlands, due to the higher absolute savings potential under colder climates and higher renovation rates. Compared to the projections with fixed renovation rates in B-LR and B-HR, the B-SD and B-ID scenarios for the Netherlands are characterized by anticipated timing in energy demand reductions, with implications on saved energy. In Spain, estimated energy reductions in B-SD and B-ID are lower compared to the B-LR and B-HR scenarios, indicating a potential effect of renovation barriers not considered in exogenous renovation projections.

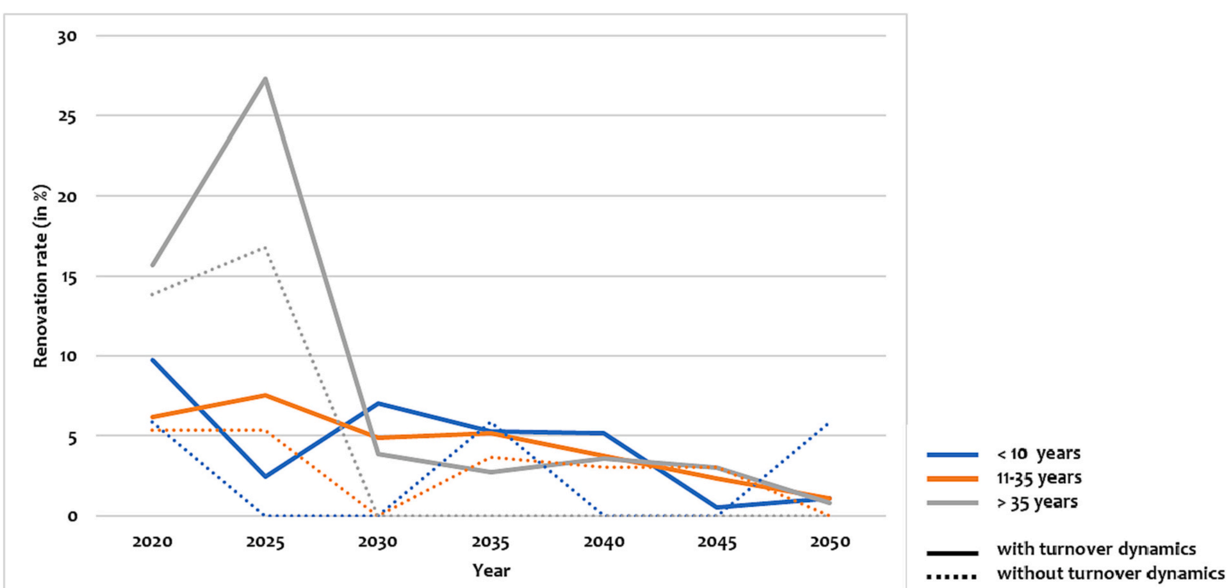

Fig. 6. Comparing household renovation decisions with(out) considering buildings stock turnover by vintage categories over time. The renovation rate (%) is presented as the percentage of households renovation within specific age cohorts (<10, 11–35, >35), relative to the total number of households in each cohort, observed over a 5-year period. An example of ID scenario in the Netherlands. Dash-lines show ID scenario without considering buildings stock turnover dynamics (B scenario).

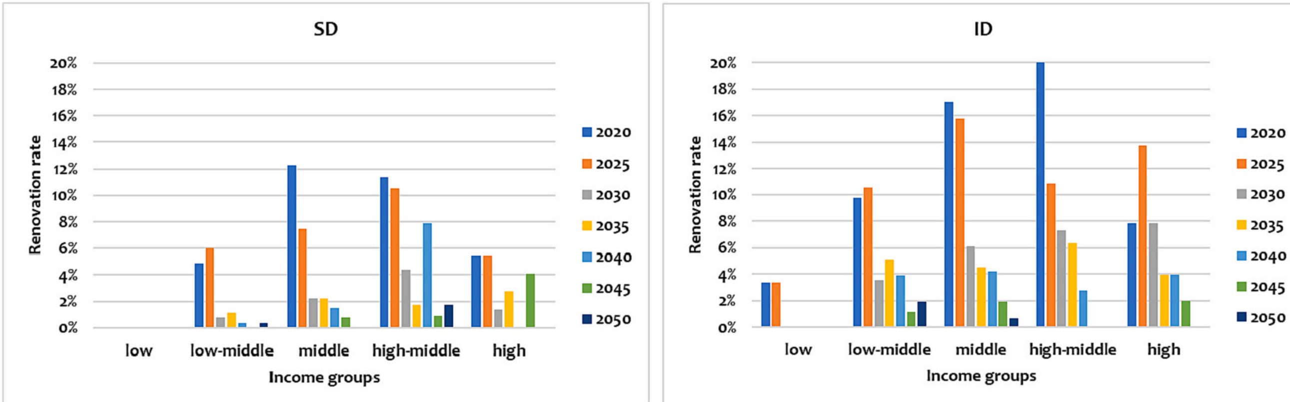

Fig. 7. Impact of social dynamics on activating households in taking renovation decisions in the Netherlands. The renovation rate (%) is presented as the percentage of households renovation within specific income group, observed over a 5-year period.

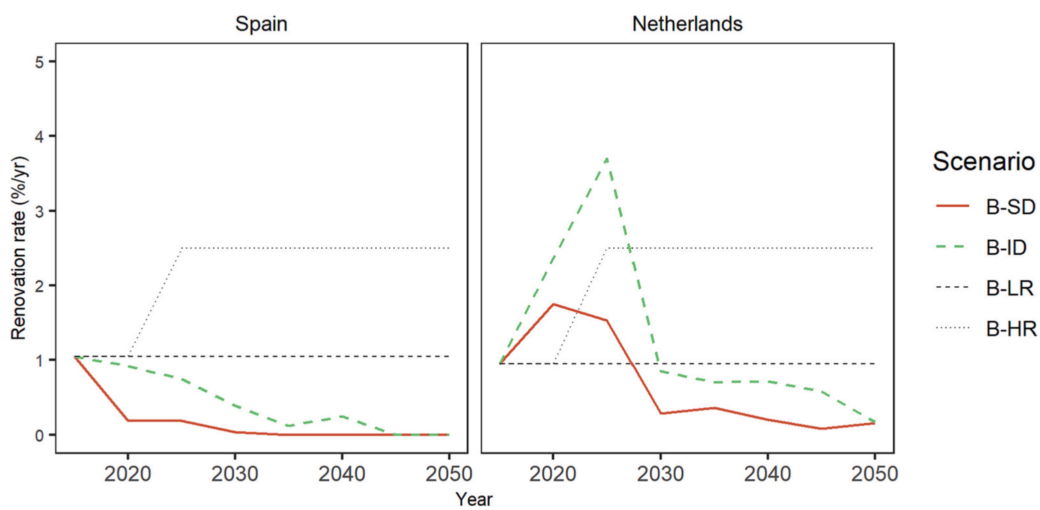

Fig. 8. Average yearly renovation rate of the housing stock over time for different scenarios in Spain and the Netherlands.

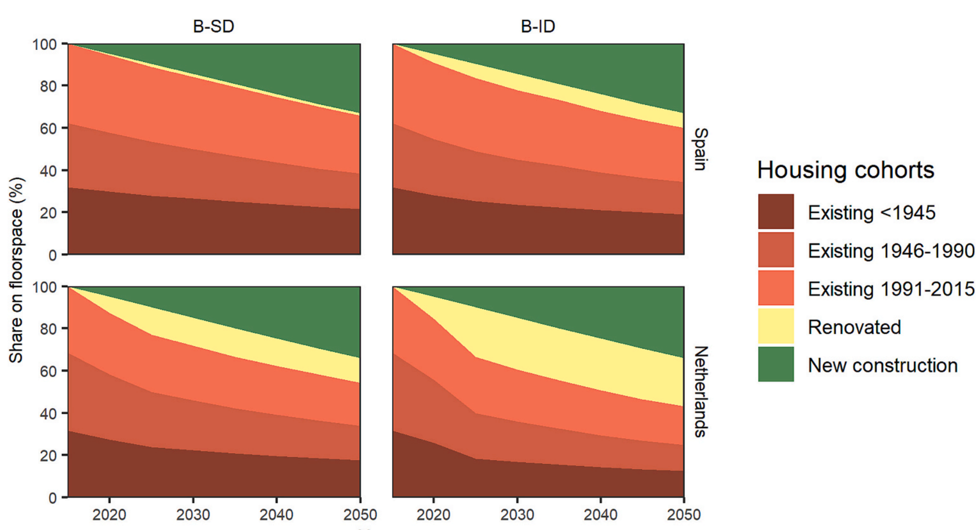

Fig. 9. Composition of the housing stock over time by energy efficiency cohorts for the B-SD and B-ID scenarios in Spain and the Netherlands. “Renovated” refers only to existing buildings renovated after the base year.

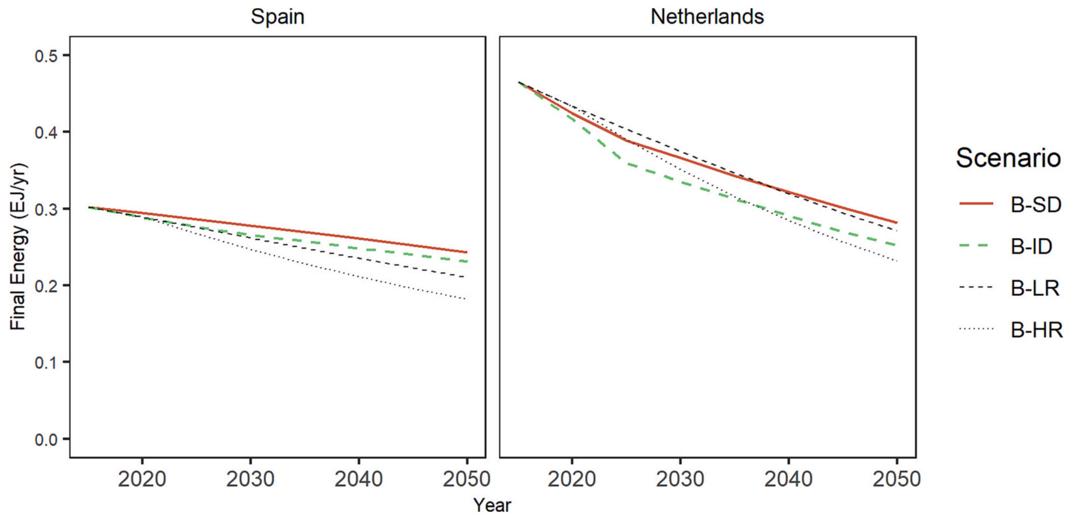

Fig. 10. Projections of total residential energy demand for space heating for different scenarios in Spain and the Netherlands.

4. Conclusion, policy implication and outlook

In the last decade, demand-side solutions, particularly the role of individual energy decisions and social norms in reducing final energy and carbon emissions, has gained considerable attention as one of the climate change mitigation strategies [1,2,22,32]. So far, IAMs have been a strong backbone and support mitigation policy assessments. These models are strong in tracing macroeconomic impacts. Still, they rely on a series of assumptions and equations that reflect past behaviour, making it challenging to integrate the heterogeneity of human decision-making, behavioural change and social interaction. ABMs complement macro-economic models (e.g. IAMs) by accommodating heterogeneity, adaptive behaviour and interactions, bounded rationality, and imperfect information [19]. In the buildings sector, while empirically-rich ABMs are strong in capturing heterogeneous adaptive behaviour and exploring non-linearities in energy decisions and energy demand reduction, they neglected the wide macroeconomics impacts as well as structural changes, e.g. building's stock turnover. Conversely, bottom-up engineering-based building sector models can represent building characteristics, technologies, and structural dynamics with great level of detail, but are limited in capturing social and behavioural changes. Thus, in this study, we take two models -BENCH ABM and MESSAGEix-Buildings, buildings module of the MESSAGEix IAM- as an example to systematically examine model integration to exploit their strengths and overcome their weaknesses. We introduce a step-wise approach to examine the feasibility of models integration and address critical methodological challenges: **a) from static to building stock turnover dynamics**: the static buildings in BENCH are updated based on MESSAGEix-Buildings stock turnover dynamics by introducing share of new constructions and demolished buildings overtime; **b) from perfect to bounded rationality**: households in the BENCH are boundedly rational due to the presence of behaviour factors. The use of the BENCH allows us to assess the impacts of pure behavioural changes, while MESSAGEix-Buildings –and in broader perspective MESSAGEix IAM– still operates in line with the rationality principles, allowing for the coherent treatment of macro-economic processes in the IAM; **c) from a fixed rate of adoption to adaptive households:** by default IAMs assume perfect information and rational expectations, omitting a variety of behavioural strategies. For example, fixed rates of renovation are commonly assigned over various buildings and time. However, households are prone to social influence and learn from their neighbours. They go through various cognitive stages of knowledge activation, motivation and consideration and may eventually decide to renovate the building. In this study we compare fixed rates of renovation with aggregated inputs from BENCH on households renovation decisions, showing that important dynamics are overlooked when assuming exogenous renovation rates.

The insights from this study offer three conclusions also as policy implications. Firstly, we underscore the significance of incorporating heterogeneity and granularity in various aspects, including households socio-demographic and dwelling characteristics, energy consumption patterns, as well as behavioural and social factors when simulating and assessing mitigation policies. Notably, we demonstrate that incorporating these elements in models introduces non-linearities over time and space. This model coupling potentially offers a platform through which we can assess the effectiveness of various mitigation strategies over time and space, ranging from social to financial incentives, in accelerating renovation rates. Secondly, this study demonstrates that considering heterogeneous household renovation decisions improves the policy advice that can be derived from buildings models. Our results show that there are many drivers that might accelerate household renovation decisions and many barriers that slow down or prevent renovation actions. Our study, in particular demonstrates that when we incorporate empirically-based heterogeneous household renovation decisions, we observe distinct scenarios compared to those based on (a range of) fixed renovation rates. One notable example is the lower estimated energy reductions in Spain in comparison to the scenarios with the fixed (high and low) rates. This suggests that various renovation barriers, including building ownership status, knowledge and awareness, motivation, and renovation cost (affordability), play a significant role in influencing these outcomes. Importantly, these factors appear to be overlooked in the existing IAM buildings module. Therefore, to effectively plan feasible renovation policies, policymakers need a deeper understanding of the key factors that significantly influence household adoption of renovation across different time periods and geographic locations. Consequently, conducting scenario testing of this nature can offer valuable insights and a more comprehensive understanding of the cases.

Finally, to set up feasible policies, policymakers would benefit from decision support tools that go beyond representation of households as perfectly-informed optimizers. To see substantial changes in residential buildings energy demand, we need localised policy packages. This policy package is a mix of various interventions, from soft information and nudge policies, such as advertisement, information campaigns, investment in education, and social interventions aiming to raise knowledge, awareness and motivation, to financial incentives, such as carbon pricing, subsidies and loans.

Future work goes towards two main directions: *advancing model integration and scenarios* and *broadening spatial scale*. From the *model integration and scenarios perspective*, the very next step involves the completion of the dynamic loops, specifically the interaction sequence of ABM to IAM and back to ABM. This is crucial for establishing a holistic model. In particular, we are keen on linking building demolition with renovation activities (e.g. through the extension of their lifetimes). In addition, future work could focus on enabling the evaluation of price-based and information policies jointly at multiple scales, which requires further MESSAGEix IAM modules integration. Furthermore, there is an opportunity to explore the inclusion of institutional interventions, involving property owners and companies, as well as barriers and enablers of energy efficiency interventions, to enrich the narratives within our BENCH model and expand the horizons of our investigative efforts. We also envision further mapping of various household groups between BENCH and MESSAGEix-Buildings. This enhancement would enable more comprehensive tracking of diverse energy efficiency interventions and energy demands. From the *spatial scale perspective*, expanding and calibrating BENCH AMB in more EU countries would improve model accuracy, in particular when examining international and regional policies, e.g. EU Green Deal, impacts.

CRediT authorship contribution statement

Leila Niamir: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Alessio Mastrucci:** Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Bas van Ruijven:** Investigation, Writing – review & editing.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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