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Research article

Incorporating social mechanisms in energy decarbonisation modelling

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ABSTRACT

The achievement of national pledges that are compatible with the Paris Agreements warming limit of 1.5C is a massive challenge, as it requires not only an acceleration of technological innovation, but also a socio-economic and cultural transformation. Reducing uncertainties demands a better integration of behavioural evolutions in models exploring future energy pathways, including non-monetary barriers and drivers to technology diffusion. This study provides suggestions on incorporating social mechanisms of change such as resistance to change and the diffusion of environmental values into a UK-focused probabilistic energy system model, with a focus on people's attitudes towards residential heating technologies. We also offer a comprehensive literature review on interdisciplinary energy transitions modelling and exploratory scenarios embedding climate risks perceptions. We argue that efficient policy-making to meeting net-zero emissions targets must fully embrace whole-system approaches, support the more constrained segments of society, and account for interconnected socio-political factors.

1. Introduction

1.1. *Societal unknowns on the pathway to net zero*

Worldwide, countries are setting emissions targets with various levels of ambition to develop their economies while aiming to avoid significant impacts from climate disruptions. The climate action tracker surveys how current nationally defined contributions (NDCs) align with the Paris Agreement target of limiting warming to well-below 2 °C (CAT 2022). While COP26 has refocused the objective to aim for 1.5 °C, most national policies currently fall under the categories of "highly insufficient" to "critically insufficient". The UK, which was the first G20 country (in June 2019) to legislate the decarbonisation of its economy and pledge to become "net-zero carbon" by 2050, currently benefits from an "almost sufficient" ranking (CAT 2022), but still faces very significant challenges in setting a sufficient pace of delivery to meet those objectives.

Independent Government advisers like the UK's Climate Change Committee (CCC) regularly review achievements to date and provide detailed periodic and long-term recommendations (Climate Change Committee (CCC) 2022). In order to know how to reach normative targets towards net-zero carbon, most decision making is informed by techno-economic energy transition models offering optimal pathways (BEIS, 2021). Often cost-optimizing in nature, these models offer high levels of techno-economic details, but much less representation of "intangible" or "non-monetary" values, despite their potentially significant effect on technology uptakes

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(Michelsen and Madlener, 2016).

Because of the number of institutions and actors involved, the UK energy transition is a co-evolution of complex and interconnected social, political, technical, environmental, and economic systems (Cherp et al., 2018). From the first stages of resource extraction to our everyday demand for energy services, social factors are deeply rooted to many aspects of the energy system. A network of causal relationships and feedback mechanisms dictates the evolution of these systems, and there is significant uncertainty on the pathways those mechanisms are likely to follow in the future.

In particular, the overarching effect of societal and behavioural change on the transition – the evolution, over time, of attitudes and preferences of people as both voters for new policies, and consumers of new technologies and services, has not often been considered (Creutzig et al., 2016).

There is growing acknowledgement, notably at the government level, of the need to encompass evolving social norms and stronger demand side action. The “net zero societal change analysis” commissioned by the Department of Business, Energy and Industrial Strategy (BEIS) emphasizes the urgency and importance of societal change. Their findings highlight the need for further research into representing behaviours in model, which has been “under-represented in prominent scenario studies in part because of the technical challenge of incorporating endogenous behaviour” within traditional models (Catapult’, 2021).

Because the Nationally Determined Contributions (NDCs)’s level of ambition in most countries, including the UK, is not currently aligned with the Paris agreement’s goals, there is mounting pressure to decarbonise in an ever-shorter amount of time (Change, 2021). The necessity for behaviour and societal changes to support technological diffusion is now an essential feature of the latest advisory bodies net-zero scenarios, though mostly represented through exogenous (external input) rather than endogenous (internal feedback loops) mechanisms. The CCC rely on “rapid changes in consumption behaviours” (Carmichael, 2019) and the IEA on the “active involvement” of consumers in low-carbon technology diffusion to reach our legally set targets (IEA 2021), along with the rapid scale-up of carbon capture and storage (CCS) technologies to deal with hard-to-decarbonise sectors, which will account for the hardest 20% of emissions to abate.

1.2. Challenges in the residential sector

Buildings are generally considered as a hard-to-abate sector because of the large-scale infrastructure changes, as well as the direct costs and impacts to consumers it would entail. While the electricity generation sector is decarbonising fast, far less progress has been made in the building sector (CCC, 2020). Approximately 90% of the 28 million households in the UK use fossil fuels – mostly natural gas – for space heating, hot water and cooking. Heating represents 74% of building emissions and 23% of all emissions in the UK (BEIS, UK hydrogen strategy 2021).

BEIS’s Heat and Building net zero strategy states that “virtually all heat in buildings will need to be decarbonised” to meet net zero targets (BEIS 2021). While the importance of using whole-systems approaches to implement energy transitions is emphasized, there is little mention of the potential effects of consumers involvement and societal change in the report. However, societal and even “just” transitions are implicitly, yet strongly evoked as part of their “five core principles to guide action” which feature an engagement to “target support to enable action for those in most need”.

Despite the difficulty to predict and quantify the evolution of people’s preferences and consumption behaviours, an improved, if imperfect, representation of their effect on low-carbon technology diffusion in the residential sector is warranted to explore potential future energy pathways and better inform our ability and options to meet net-zero targets.

The following study offers a way to model some of the main non-monetary constraints and drivers of adopting new heating technologies in a UK case study. For this, we have used survey data collected and quantified under the REEEM project (Li et al., 2018) and incorporated them into the probabilistic STET model BLUE (Behaviour, Lifestyles and Uncertainty Energy) (Li and Strachan, 2019). We describe in the modelling section the methodology used to endogenize the concepts of “resistance to change” and “societal diffusion” (understood here as the diffusion of environmental behaviours within different social groups from niche to mainstream). By providing steps towards concrete interdisciplinary modelling solutions, we contribute to fill an identified research gap on the inclusion of social mechanisms of change in energy systems modelling, engage in the conversation around bridging techno-economic and social disciplines, and also touch upon equitable transitions by taking into consideration the more constrained social segments of society.

The resulting model is designed for exploratory modelling (exploration of potential pathways) rather than attempting to predict optimal pathways based on performance trade-offs,and could inform policy-making conversations around non-linear, complex systems.

In the next sections, we review the growing literature on modelling socio-technical energy transitions (STET), highlight important related social mechanisms of change, then present the research methodology and data used. Finally, a set of exploratory socio-technical scenarios is described, demonstrating the potential influence of non-monetary systems on reaching decarbonisation targets. The discussion and conclusion sections feature a critical analysis and reflects on further avenues for research.

2. Literature review

2.1. Sustainability transition modelling

Decarbonising the energy system to net-zero is an unprecedented challenge for policy at the national and global levels (Rogelj et al., 2016). The latest scenarios detailing efforts needed to secure a maximum warming of 1.5 °C either feature large amounts of negative emission technologies (which allow some sectors of the economy and societal groups to still emit) (Minx et al., 2018; Sanchez and

Kammen, 2016), or radical demand changes (van Vuuren et al., 2018; Grubler et al., 2018). So far, conventional energy-economic modelling of deep decarbonisation has focused on 3 axes: macro-economic interactions, technological detail, and (economic) responses of consumers (Hourcade et al., 2006). These models – Integrated assessment models (IAM) at a global scale (Weyant, 2017) or energy system models (ESMs) at a national scale (Waisman et al., 2019) – continue to provide the key inputs to policy. However, conventional energy modelling inevitably has a narrower focus on technologies, pricing and environmental interactions (Trutnevyte et al., 2012). These tools also generally focus on normative analysis (back-casting) to an energy target, rather than exploring what will happen within the coevolving complexities of any pathway (Hughes and Strachan, 2010). A consensus is emerging that decarbonisation strategies must not only encompass radical techno-economic change but also incorporate societal and political dimensions (Creutzig et al., 2016).

Sustainability transitions has emerged as a field of research within the last 15 years, combining insights from innovation theory, evolutionary economics and social studies of technology, to analyse fundamental shifts in socio-technical systems (Markard et al., 2012). Derivated models investigate the multi-level, complex transformations bringing about new cultural norms (Moallemi and de Haan, 2019; Holtz et al., 2015). For instance, exploratory modelling, an emerging computational approach, is used to help cope with and address the "uncertainty space", test hypotheses and present potential pathways of change (Moallemi and Malekpour, 2018; Kohler, 2019). Distinct from simulations models focused on making scenarios predictions, parameters are assessed over possible value ranges with a focus on the endogenous workings of the system, giving insights into the causal factors that may generate certain transition pathways (Moallemi and de Haan, 2019).

This study is embedded in socio-technical energy transitions (STET) scholarship, a growing area of sustainability transitions research that has focussed on analysing the social, technological, economic and political changes that may be needed for a transition to secure, affordable and sustainable energy systems (Verbong and Geels, 2007). This area is also strongly linked to exploring novel approaches to modelling. The conceptualisation and definition of STET is broad, covering the multi-level perspective (Geels and Schot, 2007), co-evolutionary theories (Safarzyńska et al., 2012), the application of complexity science (Bale et al., 2015) and the use of adaptive policy pathways (Kwakkel et al., 2015). STET analysis has been applied to understand recent historical energy system transition processes (Geels et al., 2016) and potential future energy system transitions (Chilvers et al., 2018), although modelling is only one of many methodological approaches (Köhler et al., 2019).

A STET model needs to have some depiction (however stylised) of underpinning techno-economic characteristics, at least a disaggregation of technology options (price and technical characteristics), and operational or resource constraints of an energy system (Li et al., 2015). Others have emphasized the need to combine techno-economics with socio-technical and political perspectives (Cherp et al., 2018), and proposed a meta-theoretical framework which combines techno-economics with consumers/agents, socio-technical change and political feasibility/consistency. Agents are not just different suppliers and consumers in the energy system, but also policymakers, regulators, and civil society bodies (Mekhdiev and Victoria, 2018). STET explores societal change, which relies both on behavioural change as well as on cultural practices (Hansen, 2018), including transition dynamics, tipping points, and radical or sudden shifts.

2.2. Social mechanisms of change

In this interdisciplinary study we engage with deeply interlinked social mechanisms of change, including behaviours in decision-making, change and resistance to change, consumer and technology acceptance, and the social diffusion of environmental values.

Decision-making research has traditionally followed the approach of the "rational" actor, whose responses are mostly based on personal cost and benefits, but evidence points to human behaviours as also based on other actors' reactions (Byerly et al., 2018; Nyborg et al., 2016). Early on, behavioural studies stemming from psychology, economics and neuroscience hinted that decision making was also influenced by cognitive biases (Tversky and Kahneman, 1974). Byerly et al., who highlight the negative accumulated effects of lifestyle and household decisions on the environment, indeed emphasize the importance of the decision context in which people evolve, and that adjustments to decisions settings and social influence (nudging) can reinforce pro-environmental behaviours (Byerly et al., 2018).

At the organisational management level, decision-making research has focused on change and how to alleviate resistance to change. While change was initially considered as incremental, episodic and linear (Lines et al., 2015), it is described by Marrewijk as continuous, uncertain, stemming equally from top-down and bottom-up levels, and ultimately as a "multi-level and multi-author process in which resistance is an integral part" (van Marrewijk, 2018). Similarly, studies on the process of resistance initially focused on "controlling" resisters (Lines et al., 2015; Fiedler, 2010), while critical management studies have helped reducing the distance between agents of change and resisters, towards seeing resistance as a process simultaneously enabling and constraining change (Ford et al., 2008; Mumby, 2005; van Marrewijk, 2018).

In technology and energy transition studies, change, resistance to change and individual decision making has often been studied under the concept of public "acceptance" and "rejection" of environmental policies, which could prevent the adoption and implementation of sustainable energies (Huijts et al., 2012). Closer to the present study, consumer acceptance or resistance specifically represents the purchasing responses to the availability of new technologies (Huijts et al., 2012). Clausen and Fichter highlights market push, cost-benefit ratio and confidence (including social networks and word of mouth effects) as meta factors explaining the diffusion of innovations beyond their niche (Clausen and Fichter, 2019). Huijts et al. further develop that the intention to support or resist green energy technologies depends on attitudes, socials norms, perceived control, and personal norms; and that if people are not familiar with a technology, trust in other actors and institutions play a bigger role in the outcome (Huijts et al., 2012).

Beyond individual based decision making, social acceptance more recently also represented the broader acceptance in society of different forms of energy supply. Wustenhagen et al. and Sovacool et al. suggest that acceptance encompasses socio-political, community and market dimensions that must be met together for a joint adoption of renewables by investors and users (Wüstenhagen et al., 2007; Sovacool and Lakshmi Ratan, 2012).

The diffusion of energy technologies is inherently bound to the lifecycle of related infrastructures, which make their diffusion more complex than other products (Wüstenhagen et al., 2007). Nevertheless, the diffusion of innovation theory (Rogers, 1995, 2003) has underpinned much of the behavioural transition research space because it provides dynamic, long-term and predictive focus to the process of market acceptance of environmental innovations, notably by emphasizing their relative and competitive advantage as important variables to predicting the pace of adoption (Clausen and Fichter, 2019), influenced by adopters categories evolving through social networks of diffusion (Rogers, 2003).

2.3. Modelling arguments

Some STET practitioners have argued that formal models can provide discipline in assessing the linkages and interdependencies between actors and other elements within a transition (Holtz et al., 2015). Others warn of the difficulties of trying to integrate detailed, context specific or historically rich and nuanced qualitative, socio-technical analysis with quantitative modelling approaches (McDowall and Geels, 2017). Similarly, the net zero societal strategy (Catapult', 2021), while confirming that societal change and the workings of energy service demands evolutions was underrepresented in prominent scenarios and models, identified that "adding increasing sophistication" like endogenous behaviours into current models is not always the solution because of difficulties in applying costs to shifts in values change. Instead, they hint at the value of making modelling practices evolve and use different tools and approaches to improve the representation of societal change "in or alongside" modelling.

Trutnevyte et al. reviewed the rising contributions in quantitative modelling and transitions theories frameworks in energy and climate research (Trutnevyte et al., 2019). They argue that three approaches have been used – iterating (scenarios into model), bridging (successive contact points between approaches) or merging (new models). Hirt et al. also stress that much work to date has been interdisciplinary learning, rather than on behavioural realism or on solutions to energy and climate challenges (Hirt et al., 2020). Proponents of the merging approach have argued specifically for an agent based methodology (ABM) (Hansen et al., 2019) or a systems dynamics methodology (Mekhdiev and Victoria, 2018; Freeman, 2021).

System Dynamics (SD) is a modelling method initially designed for industrial applications (Forrester, 1961) then urban dynamics before having a breakthrough in global environmental systems via Donella Meadows "Limits to growth" (Meadows, 1972). SD models are based on flows, causal loops and delays, alleviating the difficulty to capturing feedback dynamics in large-scale transitions. Complex societal systems presents evolving, non-linear behaviours, and actions to stabilize them often lead to unintended consequences such as "policy resistance", the tendency for policy interventions to be delayed, diluted or defeated by the response of the system to the intervention itself (Groping in the dark 1982; Sterman, 2000). Qualitative data have been early on recognised as important to model decision-making in SD (Forrester, 1961), and the method provides formal means to represent social mechanisms (Sterman, 2000; Lane and Oliva, 1998; Verrier et al., 2022) as called for in transitions research (Geels and Schot, 2007; Geels et al., 2016). SD is gathering increasing interest in socio-technical transition research (Papachristos, 2019) and socio-technical energy transition modelling (Li, 2017; Freeman, 2020), in a bid to enhance traditional techno-economic orientated modelling and scenarios. The application of SD to STET analysis and modelling is further detailed by Papachristos (2019).

Only a few studies have attempted to create new STET models that fully merge transition frameworks and quantitative modelling. Those that do include a very well-developed model combining systems dynamics and ABM with a particular focus on lifestyle change and transport options (Köhler et al., 2009), a stylised techno-behavioural model of feedbacks between technology learning, evolving preferences and network effects for tipping points in complex sociotechnical systems (Tran, 2016), and a novel formal behavioural-evolutionary macroeconomic model, that tracks coevolution of four agents populations: consumers, producers, power plants and banks, interacting through interconnected networks (Safarzyńska and van den Bergh, 2017). Other examples include Tempest, a novel societal change and political agency energy transition model (Freeman, 2021), and BLUE, the model used in this research, which is an energy systems simulation model with non-optimal decision makers of heterogeneous consumers and firms, plus stylised depictions of political consistency and societal shifts (Li and Strachan, 2019; Li, 2017).

We present in the next section the model and survey study that were used as the basis of our project, including general updates to technology market data (up to 2021) and to diffusion terminologies.

3. Methodological background

3.1. The BLUE model

3.1.1. Overview and structure

BLUE (Behavioural, Lifestyles and Uncertainty Energy Model) is a non-linear socio-technical energy transitions (STET) model of the UK energy system, capturing technological change, energy use, and emissions over the 2010–2070 timeframe horizon. It features imperfect decision-making in investments and captures uncertainty using a probabilistic approach based on Monte-Carlo analyses with uniform distributions; detailed mathematical descriptions were provided by Li (2017) and furthered in Li and Strachan (2019). BLUE conducts exploratory scenario analyses rather than proposing optimal pathways for set normative targets.

While the original model followed the typology of the Multi-level perspective framework (Geels and Schot, 2007), the version for this study is presented under the three perspective framework developed by Cherp et al. (2018), to emphasize the socio-technical and socio-political perspectives that are added endogenously to the techno-economic perspective (Fig. 1) .

As the capital stock in each sector ages and needs replacing, actors across the energy system are responsible for stock replacement. On the supply side, actors are responsible for balancing energy demand and supply in the electricity and the hydrogen systems, while on the demand side, each sector (including residential, industrial, and transport) is represented by different actor types. Actors do not possess advance knowledge of changes to landscape conditions such as fuel prices, social preferences, or technology performance and costs, so their decisions are based on bounded rationality. Carbon values and fuel costs in BLUE have been updated up to 2020 (BEIS 2018), allowing calibration both to 2010 and to 2020.

3.1.2. Model decision variables

The model's indices include system-wide parameters, notably the level of global climate ambition and a UK demand driver. The global ambition (low, moderate or high) determine internationally set fuel price paths and UK technology capital costs (a higher global ambition sets higher fossil fuel prices and lower new technologies prices) based on BEIS fossil fuel prices forecasts (BEIS, 2020). The demand driver influences the level of demand growth per sector and the flexibility to shift loads at peak times. Sectoral energy service demand growth estimations are underpinned by BEIS Energy and Emissions projections (BEIS 2020), household disposable income and growth rate projections from the Office for National Statistics time series and Office for Budget Responsibility (OBR 2019).

Actors can be configured with a set of default behavioural parameters including market heterogeneity (degree of cost optimising behaviour, which affects the extent to which costs alone drive actor's decisions), demand elasticities (sensitivity to changes in energy prices), hurdle rates (sensitivity to up-front investments, which can indicate how different actors value the present compared to the future and their resulting investments attitudes), and intangible costs to capture other non-monetary cost or benefits. In addition of the capital and fuel costs, these parameters influence actor's estimated net present value (NPV) and their resulting choice for each technology replacement. In the extension of the model presented later, the NPV remains an important value providing direction to the system under certain conditions.

The technologies available to choose from in the residential heating sectors include gas boilers, hydrogen boilers, electric resistive heating, and air source heat pumps.

3.1.3. Societal groups and diffusion of innovations

The general population representation is based on Rogers' well-established diffusion of innovations (Rogers, 2003), where consumer segments are distributed along a normal distribution of adoption propensities, from least to most risk averse (Edelenbosch et al., 2018; Axsen and Kurani, 2012; Pettifor et al., 2017). Society is divided in five groups, and each demand actor in the model is assumed to share the characteristics of one of those segments. The first individuals to adopt a new trend or product are labelled innovators and early adopters, who represent 2.5% and 13.5% respectively of the population or market share and have high adoption propensities and high risk tolerance. They are followed by the early majority (34%), late majority (34%) and laggards (16%), who are increasingly risk averse (Li, 2017; Axsen and Kurani, 2012).

The terminology of the social groups has been updated in this study to very low-carbon ready, low-carbon ready, partly low-carbon ready, constrained and very constrained. This is to encompass other well-recognised frameworks such as the COM-B model of behavioural change emphasizing capability, motivation and opportunity as interlinked to actual behaviour (Michie et al., 2011), and inspired by ongoing work by H. Pettifer and C. Wilson defining citizens as belonging to either resourceful, constrained or cautious low-carbon lifestyle clusters (Pettifor et al., 2017; McCollum et al., 2018). The behavioural parameter settings vary for each social group. In this study, we use those presented by Li and Strachan (2019, 2017) adapted to our new terminology (Table 1).

The original model and current extension have been created with Analytica, a visual modelling platform providing array abstraction capabilities (Analytica 2022). Therefore, BLUE's strengths include multi-dimensional uncertainty analyses, thanks to indices which automatically propagate any change of characteristics in the whole model (Welch, 2017). In addition, while BLUE is not a full System Dynamics model, the platform allowed to respect System Dynamics principles including dynamic variables and the endogenization of reinforcing feedback loops, particularly important to the present study. It is sometimes argued that Analytica is a judicious choice to design System Dynamics models containing a large amount of indices (or "subscripts") (Welch, 2017).

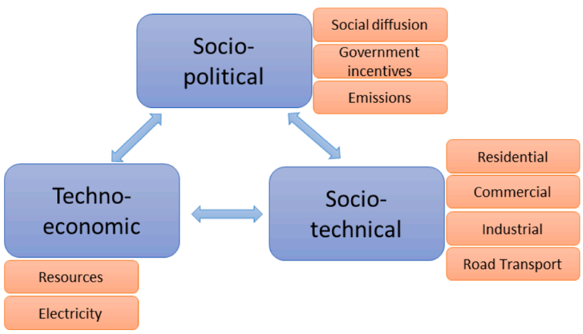

Fig. 1. Model structure.

3.2. The REEEM study

The present study relies on the qualitative data obtained under the REEEM project (REEEM 2022). Conducted in 2018, it used a Discrete Choice Modelling approach (Multinomial logistic models (MNLM) were developed) to investigate which factors are most influential in residential heating systems and vehicle technology choices in three countries (UK, Finland, Croatia). The discrete choice modelling shows choice behaviour as a set of preferences, where consumers are assumed to choose preferred available outcomes to maximise their own utility (Ben-Akiva and Lerman, 1985). We use specifically the results obtained for the UK heating sector, collected from over 1000 households, for which the MNLM analysis finds a very strong correlation between people's existing ownership of a heating system and their choice of a future heating technology. We relate this to the phenomenon of "resistance to change", an initial, natural reluctance to adapt that has been defined as the tendency for behavioural attitudes to continue on a similar path following a change in environmental conditions (Luiz et al., 2020; Craig et al., 2014).

4. Integration of socio-technical and socio-political behavioural mechanisms

In this section we detail the approach taken to integrate a behavioural survey dataset from the REEEM project within the techno-economic based model BLUE. The selected data show public preferences which affect replacement choices in residential heating technologies. Our objective is to provide concrete steps to represent some of the dynamic, non-monetary barriers and levers identified in the literature, with a focus on resistance to change and the diffusion of environmental values throughout society. The variable of focus is the evolution of the technology portfolio for residential heating.

4.1. Selection and incorporation of data representing resistance to change

The REEEM findings show and quantify how the knowledge and experience people have with a technology influence the evaluation of this technology (Huijts et al., 2012). We see in the details of the data that previous experience and familiarity with a technology creates an attachment that has a striking influence on people's choices in a future heating system. Fig. 2 specifically presents the likely choices towards each replacement technology based on the previously owned technology. Regardless of changing costs and performance values, 77% of UK respondents who already have a gas boiler system are found to select a gas boiler again, and the figure is at more than 60% for electric heat pumps (HP). Conversely, for a householder in the UK possessing a gas boiler, there is only a 6% likelihood of choosing an electric resistive heater, 8% an electric heat pump, and 9% a solid/biomass-fuelled appliance.

We consider these data as a representation of a major behavioural, non-monetary barrier to adopting new technologies and decided to incorporate them into BLUE as a quantified representation of the phenomenon of resistance to change. However, the data could not be transferred directly into the behavioural parameters already existing in the model, so a new dynamic feedback loop representing choices and preferences had to be created (the "preference loop" or "baseline loop"). This new loop is centred around the variable "technology portfolio residential heating", which provides for each year of the time horizon (for each time step) the percentage of market share for each heating technology featured in the model.

The loop is based on the idea that the market share of each technology in the previous year (or time step) [t-1] can provide a quantification of the distribution of "previously owned technologies". Equally, every year the technologies can be redistributed following the REEEM preferences data towards any of the technologies available, providing a picture of the market share distribution for the current year [t]. In other words, in this configuration, each technology's market share value in the year [t] will be fed by its own value at [t-1] associated to the redistribution preferences highlighted in Fig. 2.

The process was created in two main steps. The technology market share for technology *a* is first multiplied by its probability to be redistributed towards each technology *a, b, c, d*. Available technologies are organised in a table list ("index"), so the calculation returns a new table where the shares of previous technologies are already multiplied by their redistribution probabilities, i.e. by the proportion

Table 1
Summary of behavioural parameters for each social group, adapted from Li and Strachan (2019, 2017).

Societal group	Initial population proportion	Discount rate for decision-making	Sensitivity to cost(Market Heterogeneity v)	Intangible costs perception
Very low-carbon ready/Innovators	2.5%	3% Highly values the future, long-term perspective on investments	0–4 Principally motivated by non-price factors	Ignore intangible costs associated to new and unfamiliar technologies
Low-carbon ready/ Early adopters	13.5%	5%	5–9 Price conscious but large cost savings required to shift	Perceive half of average
Partly low-carbon ready/Early majority	34%	10%		Perceive average level
Low-carbon constrained/Late majority	34%	15%	10–19 React strongly to price, but cost is not the only decision factor	Perceive 1.5 times the costs
Very low-carbon constrained/ Laggards	16%	20% Short term, individual perspective on investments	10–50 Choose the least-cost option	Perceived as twice as large

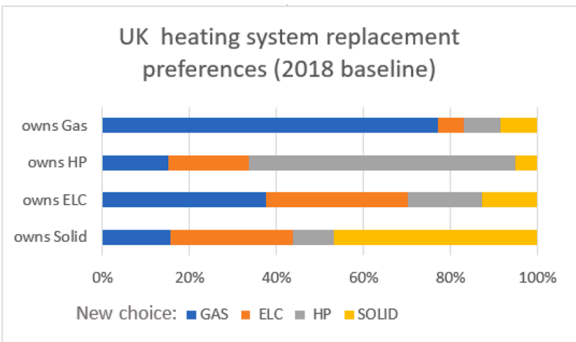

Fig. 2. Quantified influence of existing ownership on future heating systems choices in the UK residential sector.

of the share sent towards new technology choices in the next year (Fig. 3, step 1). The second step consists of summing the newly acquired shares for each technology to obtain the total share at time step [t] (see step 2 in Fig. 3 and Appendix A).

The values from step 2 are then fed into the calculation of the technologies market share for the following year, creating the dynamic "baseline" loop of surveyed public preferences. For the loop to work, a time offset must be added before values from time step [t-1] are sent toward the market share evaluation at [t].

The baseline loop, which temporarily bypasses other decision-making parameters in BLUE, represents how the behavioural effect of "resistance to change" can, in this configuration, slow down the uptake of new or in-development technologies. The regular decision making in Blue, which aims to overcome the baseline loop over time, is based on the NPV value taking into consideration behavioural parameters such as the level of sensitivity to capital costs (Table 1). How long the NPV-based parameters will need to take over, and how strong pro-environmental consumption behaviours will be in the NPV, will depend on the pace at which environmental values spread throughout society. A snapshot of this socio-technical focused model extension, connecting the baseline loop to NPV-based choices, is available in Appendix B.

4.2. *Representation of the societal diffusion of pro-environmental consumer values*

This part of the modelling aims to represent how the barrier created by the baseline loop can be overcome by the diffusion of low-carbon transition ideas and environmental values throughout different segments of society. When a larger proportion of the population becomes "low-carbon ready" (more sensitive to environmental values and able to support them as consumers), it is assumed that consumers are getting more responsive to green technology developments and evolving niche market trends. The diffusion is driven by a drift rate and when it eventually reaches a threshold, the redistribution preferences surveyed in REEEM are entirely outweighed by the NPV-based choice. The threshold is currently set at half the population being at least "partly low-carbon ready", indicating a majority of the population holds values that are assumed as able to overcome resistance effects and accelerate the NPV choice towards

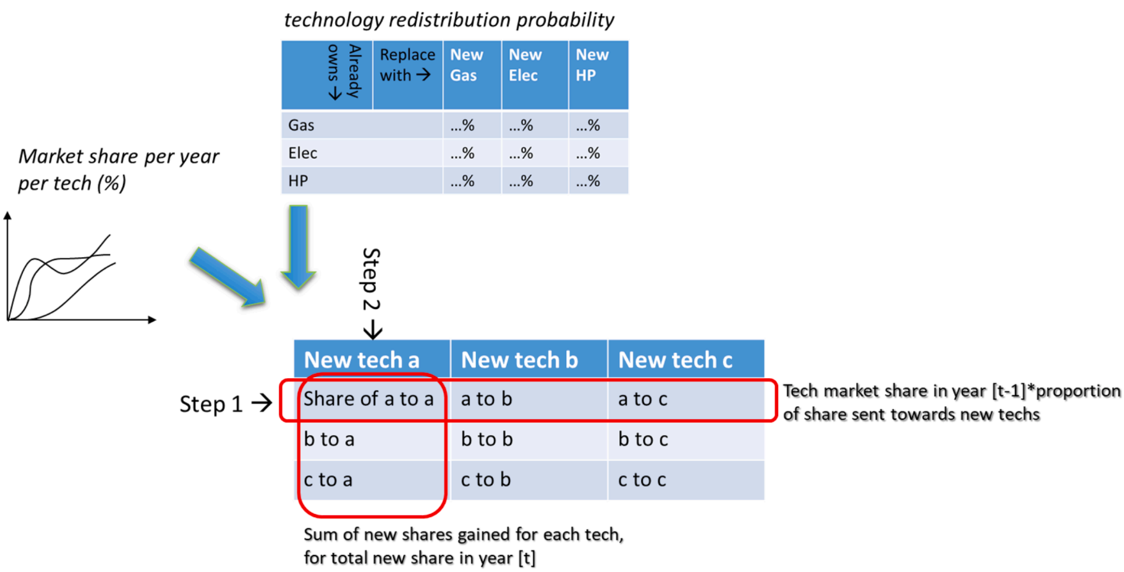

Fig. 3. Two-steps incorporation of public preferences into a market share redistribution loop.

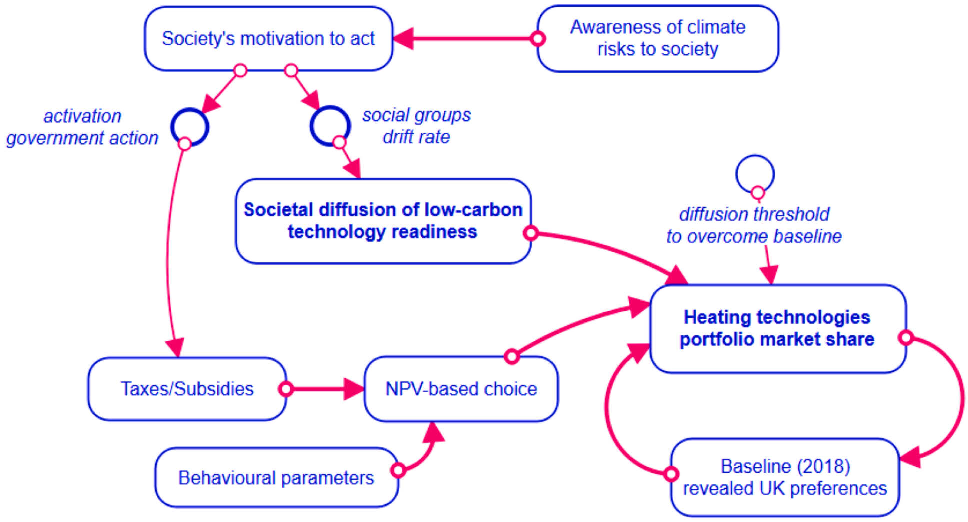

Fig. 4. Graphical summary of model extension features.

decarbonisation.

To model this change, a dynamic variable is created to make the proportions of the societal groups evolve over time with the assumption that the population steadily moves towards increasing low-carbon readiness (estimated from year on year increasing levels of concerns in public's attitudes surveys (BEIS, 2020)). The "drift rate", recreating a Bass diffusion, is the percentage each category is likely to lose each year to the next category and gain from the previous category. Like for the available heating technologies, the equation is indexed by a listing of the five different social groups, so a single variable provides simultaneously the value of the "stocks" of each social group (see appendix A).

While the drift rate can be set exogenously with a uniform or triangular distribution (via option in the model and user's interface (appendix B)), its evolution can also be endogenized and informed by estimated or fully quantified data on year-on-year evolutions in climate risk awareness and climate risk impacts factors within society. This offers the potential for further exploration into driving mechanisms of change potentially influencing attitudes and consumers behaviours. These factors are:

a. Increased concern expressed in national polls
b. Growing education in climate science
c. Increase in the occurrence of locally felt impacts (e.g., heatwaves, floods, storms)

a) represents the yearly percentage point increase of the UK population thinking that climate change effects are felt in the UK at least to "some extent", b) is represented by the increase in the UK population defining themselves as overall "very" concerned about climate change, and c) by the increase in people thinking climate change already affect their local area. Available data have been extracted from the BEIS public attitude tracker surveys, which provide important insights into changing perceptions on energy and climate amongst the UK public (BEIS, 2019, 2020), then turned into uniform distributions to account both for historical data and uncertainty in the future.

These factors represent the level of risks perceived by society, so we consider that their average can serve as proxy for ranking the overall national "social motivation to act". This variable is derived from the concept of "public willingness to act", representing here a sense of responsibility or "imperative" to act towards transitions (Freeman, 2021). Via the social motivation to act, the risks perceived by the public also determine if the government considers it appropriate to take action by imposing extra taxes on fossil heating technologies. The current model imposes taxes on gas once the social motivation to act reaches a threshold level, but government actions can also be set independently, following, or not, emerging societal trends. The tax imposed, called "residential heat penalty", consists in doubling the perceived capital cost of fossil technologies in the NPV calculation.

A graphical summary made with Stella architect is presented in Fig. 4 for illustration purposes; snapshots of the model extensions made with Analytica, including the socio-political extension linking environmental values diffusion, climate risks perception and government action can be seen in appendix B.

5. Illustrative scenarios and simulation results

5.1. Scenarios setting

The scenarios presented below allow the exploratory simulation of non-monetary socio-political drivers of interest, such as the pace of societal shifts and a push-pull between society pressure and government support. They navigate around comparing shifts between

Table 2
Summary of scenarios features.

	A	B1	B2	C1	C2
Reeem baseline preferences	✓	✓	✓	✓	✓
Shift to NPV-based choices		✓	✓	✓	✓
Pace of social diffusion		constrained	constrained	fast	fast
Government support (taxes)			✓		✓

past preferences, represented by the "baseline loop" informed by the REEEM data, and newly acquired preferences, represented by the NPV-based choices, influenced by BLUE's updated behavioural parameters (Table 2).

A) 2018 REEEM data baseline preferences loop alone
B) Scenario *A*+ constrained shift to NPV-based "new preferences" (reduced diffusion drift rate for the two more constrained segments of society)
   1. no tax (government does not follow society's motivation to act)
   2. with tax on gas
C) Scenario *A* + rapid shift to NPV-based "new preferences" (fast diffusion drift rate for all social segments)
   3. no tax
   4. with tax on gas

5.2. Scenarios results

The simulation results (Fig. 5) show the evolution of the residential heating technology market share over time and cumulative probability plots of resulting direct emissions (i.e. predominantly from gas used for cooking and heating) in $MtCO_2$ (BEIS, 2022). Centred on the year 2050, the graphical representations of the cumulative distribution function show the risks probability of ending within different ranges of residual direct carbon emissions. Emission results are set to a moderate UK demand driver ("central, some flexibility") and are presented with the three levels of global ambition.

The baseline preference scenario (A) presents a very slow transition towards low carbon technologies and reserves the lion's share to gas which is currently by far the most widespread and familiar heating technology in the UK. There is only a slight steady evolution of the share of electric resistive heating and a more pronounced increase of the heat pump portfolio share over time. Emissions, which accounted for around 67 MtCO2 in 2020 (BEIS 2022), have an 80% chance of ending up within a range of 45 and 58 MtCO2 by 2050 in all three levels of global climate ambition in this scenario. The gas share does decrease, but, in the absence of additional policy push, too slowly to reach any significant low-carbon uptake and help achieve net zero carbon targets in time.

In scenarios B1 and B2, the societal diffusion kicks in, though slowly. It follows the society's motivation to act, which, based on current trends of how people perceive the climate crisis and the increase of locally felt effects, is assumed to increase steadily over the coming years (the more motivation, the higher the drift rate from a segment to another). As a result, the 2018 baseline (A) representing attachment is overcome, and more "low-carbon readiness" behavioural parameters influence the overall NPV-based choice towards novel technological uptake (B1, B2 and C1, C2).

However, we assigned a slower drift rate to the two more constrained segments of society, to represent they may be struggling to adopt new low-carbon technologies despite having similar perception of risks and motivation to act than other segments. In other terms, the social diffusion in B1 and B2 drives low-carbon uptake only in a constrained fashion, with the attachment to incumbent technologies overcome around the 2040s and gas boilers remaining dominant well into the next decade.

B1, where the government doesn't impose additional taxes or incentives on fossil fuels, shows a 50% chance that emissions have reduced below 35 $MtCO_2$ by 2050. In B2, the government enacts a tax increasing the capital cost of gas boilers, which partially compensates for the slow diffusion but struggles to bring emissions significantly down before 2060. In this scenario, the plot shows there would be an 80% chance that resulting emissions will be in the range of 23 to 35 $MtCo_2$ in 2050 for almost all global climate ambitions levels. Even if emissions are significantly reduced compared to the baseline scenario A, the delay in society's shift to low-carbon technologies presents potential significant impact to UK legally binding carbon reduction targets.

In scenarios C1 and C2, the societal diffusion fully materializes for every social segment, with no constraints applied. If the whole of society transitions quickly, more and more people belong to "low-carbon ready" groups, driving a much faster uptake of new technologies. As a result, we can observe in C1 that even with a moderate level of climate ambition and no government penalty on fossils there would be a 50% chance for residential emission to be lower than 23 $MtCo_2$ by 2050 (respectively 19 $MtCo_2$ and 27 $MtCo_2$ for the highest and lowest levels of climate ambitions). In C2, in addition of the rapid societal diffusion, the government responds to society's increased motivation to act by imposing a tax on gas, which further helps decrease the share of gas and residential emissions over time. This is our "best case" scenario, with an 80% chance a global moderate climate ambition would result in less than 20 $MtCo_2$ emissions for the residential sector in 2050, and an 30% chance for less than 15 $MtCo_2$.

In C1 and C2 significant change happen a decade earlier compared to B1 and B2, the low-carbon technology uptake is rapid, and carbon emissions reductions are significant. However, even in these ambitious scenarios, emissions fail to become negligible before the 2070s.

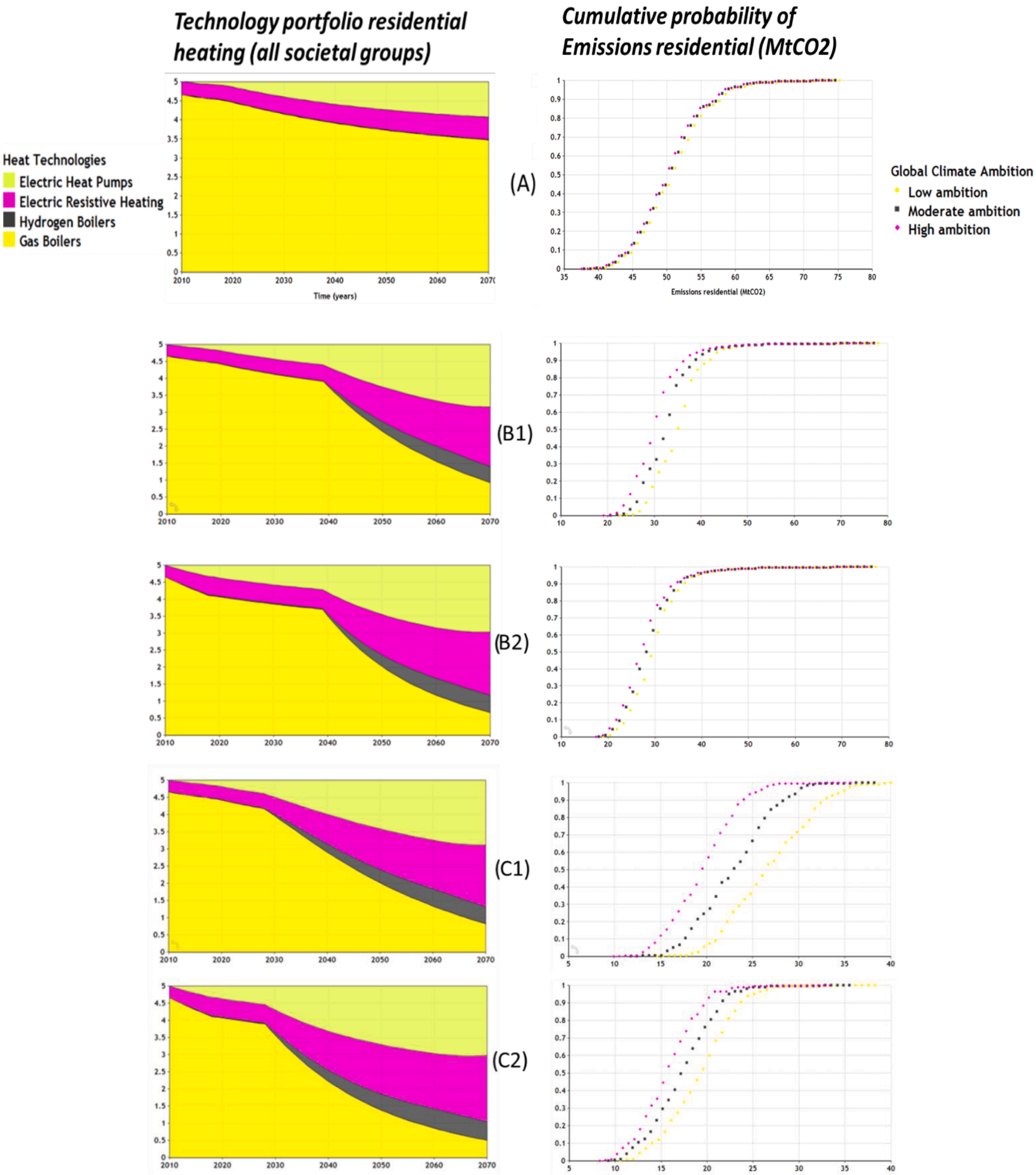

Fig. 5. Simulation results on the evolution of heating portfolio market share and residential emissions.

Analysis and discussion

This modelling offers an original approach to quantify and endogenously incorporate non-monetary factors in an energy system model, providing explorative insights into potential barriers and levers of energy transition pathways. A particular contribution is to represent how the social diffusion of environmental values can drive the uptake of technologies, rather than the other way around (market shares informing society's acceptance). Another feature of this analysis is to explicitly acknowledge, embed and analyse probabilistic uncertainty in future energy pathways. While exploratory in nature, this study amplifies recent contributions finding that the inclusion of societal parameters in energy systems models provides additional nuance in our understanding of possible national energy pathways. This has the potential to either slow down, disrupt or accelerate the course towards diverse climate mitigation objectives (Li and Strachan, 2019; Freeman, 2021; Li et al., 2018).

The model explores uncertainties where climate risks perceptions could translate into a faster diffusion of low-carbon technology readiness, or where government action, such as additional taxes on fossil-based technologies, can only partially compensate lower rates of low-carbon technology adoption. The greatest points of leverage could be through combined actions for a rapid diffusion of low-carbon readiness even for the more “constrained” segments of society (e.g. through communication campaigns and citizen’s initiatives), in line with greater motivation to act fuelled by accurate information on future local and global climate risks, and appropriate government incentives including support for appropriate infrastructure scale-up. Policy discussions could also take into consideration that while the attachment to a technology can be considered a “barrier” to change, and social movements are often seen as slowing down transitions by resisting climate policies, both aspects can on the contrary also be channelled to fasten transitions. For instance, social movements could stem from more motivation to act against climate change, and the attachment felt for familiar technologies could help emerging technologies steadily stabilize on the market.

Our study aims to concretely contribute to the conversation on improving the representation of such societal mechanisms in energy modelling. We acknowledge that it is only a step forward, not yet a comprehensive set of related feedback loops. Additional factors to be considered in further research are:

- An extension of model boundaries to the factors influencing education in climate to find new leveraging options to increase the pace of transformation
- A link between government action and communication programs (similar to those in place to inform the population during national lockdowns due to the Covid 19 pandemic)
- The creation of a more comprehensively dynamic baseline loop evolving in conjunction with technological niche developments (better representation of the familiarity and acceptability gradually gained by new entrants on the market)

Some other aspects that could be explored further concern resource scarcity or a growing awareness of the potential negative environmental, social and governance impacts provoked by the amount of materials to be extracted, despite the pressing need to accelerate the uptake of green technologies (Verrier et al., 2022). This concern can potentially be expressed throughout society by a will to reduce energy consumption, and modelling could link this aspect to demand side energy reductions as a means to accelerate decarbonisation, as was advised in a recent CREDS report (John Barrett and Betts-Davies, 2021). Future work could also improve the assumptions and representations of hydrogen, which is currently only partially treated in the baseline. The development estimations from on-site trials which are to be released in the last quarter of 2022 could feed the next iteration of the model.

As the frequency of extreme weather-related events increases, both globally and in our own local areas, it is possible that an increasing share of the population would support a radical change of consumption habits. If or when a tipping point will be reached where the majority wants climate change to be treated like an emergency crisis remains uncertain. However, a growing literature proves significant public willingness to participate in the transition and, therefore, the importance to incorporate changes in lifestyles and citizens engagement within net-zero policies and models (Xexakis and Trutnevyte, 2021; Pidgeon et al., 2014). Several climate assemblies have been organised around the world, where a representative sample of citizens is randomly selected to learn, discuss, and propose recommendations to tackle climate change. All have shown that citizens tend to propose bolder policies than those currently in place in their countries, even for policies that will directly impact them. This shows that while resistance to change can be a real challenge to rapid evolution, citizens can also accelerate diffusion through political pressure.

This study has focused on providing steps to model non-monetary barriers to adopting new heating technologies in the UK, and potential balancing levers such as a diffusion of environmental values within society from niche to mainstream driven by increased climate awareness and perceived risks. While focusing on the UK, the proposed modelling methodology is replicable to most contexts. The study highlights the importance to understand better the unintended consequences of interconnected socio-technical factors to, in turn, better inform and assess long-term policy implications. While the current model was not developed on a traditional System Dynamics platform, we would advocate for the wider use of system thinking principles and system dynamics modelling in general. These approaches are particularly appropriate to deal with nonlinear and complex social systems and are critical to solving systemic problems by improving the capability of identifying, understanding, and predicting the behaviour of systems, and finding levers to produce desired long-term effects. This can foster interdisciplinary and transparent collaborations between stakeholders to help deliver a just and rapid transition. to help a faster and more equitable transition overall – a “just” transition.

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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Technical Appendices

Appendix A: main equations (model extension)

Variable technology portfolio residential heating:

Dynamic(ResHeatTechBasePort, self [time-1]*(1-(TurnoverResHeat/100))+((TurnoverResHeat/100)*final_heatech_transf))

Inputs:
- final_heatech_transf — final heatech transfer share
- ResHeatTechBasePort — Residential Heat Tech Base Year Portfolio
- Time — Time
- TurnoverResHeat — Turnover Residential Heating

Outputs:
- heatech_share_transf — heatech share*transfer
- TechPortResHeat — Technology Portfolio Residential Heating

The "technology portfolio residential heating" is a fraction of the residential heating market indexed by technology type and by societal group. The function "dynamic" represent that the variable depends on its own base year value ("Res Heat Tech base year portfolio") as well as its value in the previous year, as if turned into a "stock" with input and output flows depending on its own stock value. The equation also considers the technology average replacement rate ("turnover residential heating") and the final redistribution choice toward a replacement technology ("final heatech transfer share"), whether this comes from the baseline loop or from the NPV-based choice.

Intermediary variables Step 1 and Step 2:

The create the baseline loop, the data selected from the REEEM survey is turned into a reference (base year) table of redistribution preferences. The values are indexed by the type of technologies considered in REEEM on the left ("current" technologies) and by the technologies available in BLUE.

Edit Table of heatech transfer base year without solid

Reeem current heat tech / Heat Technologies

	Gas Boilers	Hydrogen Boilers	Electric Resistive Heating	Electric Heat Pumps
Gas Boilers curr	0.8431	0	0.06451	0.09236
Hydrogen Boilers curr	0	1	0	0
Electric Resistive Heating curr	0.4311	0	0.3717	0.1972
Electric Heat Pumps curr	0.1579	0	0.1974	0.6447

To incorporate these with the already existing portfolio market share, Step 1 multiplies the share of each technology in the previous year by the percentage that will be redistributed towards each available technology in the next year. The equation in analytica is presented as the following indexed table:

Edit Table of heatech share*transfer

Reeem current heat tech

Gas Boilers curr	slice(TechPortResHeatSG,Heat_Techs,1)*slice(heatech_transfer_b2,Reeem_current_heat_t,1)
Hydrogen Boilers curr	slice(TechPortResHeatSG,Heat_Techs,2)*slice(heatech_transfer_b2,Reeem_current_heat_t,2)
Electric Resistive Heating curr	slice(TechPortResHeatSG,Heat_Techs,3)*slice(heatech_transfer_b2,Reeem_current_heat_t,3)
Electric Heat Pumps curr	slice(TechPortResHeatSG,Heat_Techs,4)*slice(heatech_transfer_b2,Reeem_current_heat_t,4)

Step 2 sum the shares that each future technology has gained from each of the other previously available technologies:

Edit Table of heatech transfer share

Heat Technologies

Gas Boilers	SUM(heatech_share_transf,Reeem_current_heat_t)
Hydrogen Boilers	SUM(heatech_share_transf,Reeem_current_heat_t)
Electric Resistive Heating	SUM(heatech_share_transf,Reeem_current_heat_t)
Electric Heat Pumps	SUM(heatech_share_transf,Reeem_current_heat_t)

For the loop to work, a time offset must be added before values coming from [t-1] are sent toward the market share evaluation at [t].

Diffusion through societal segments:

The variable "societal segments" is a dynamic stock variable indexed by the five possible groups. The resulting percentage value of each segment across the population depends on its value at [time −1] + the proportion gained from the previous segment - the proportion taken by the next segment

Societal segments = dynamic(Societal_Segments_ba,self [time-1] - proportion_taken_fro[time-1] + proportion_gained_in [time-1])

Proportion taken from each category =

Table(Societal_Grouping)(0,Societal_Segments*(drift_rate_to_next_s/100),Societal_Segments*(drift_rate_to_next_s/100, Societal_Segments)*(drift_rate_to_next_s/100, Societal_Segments)*(drift_rate_to_next_s/100))

Or, in its table form:

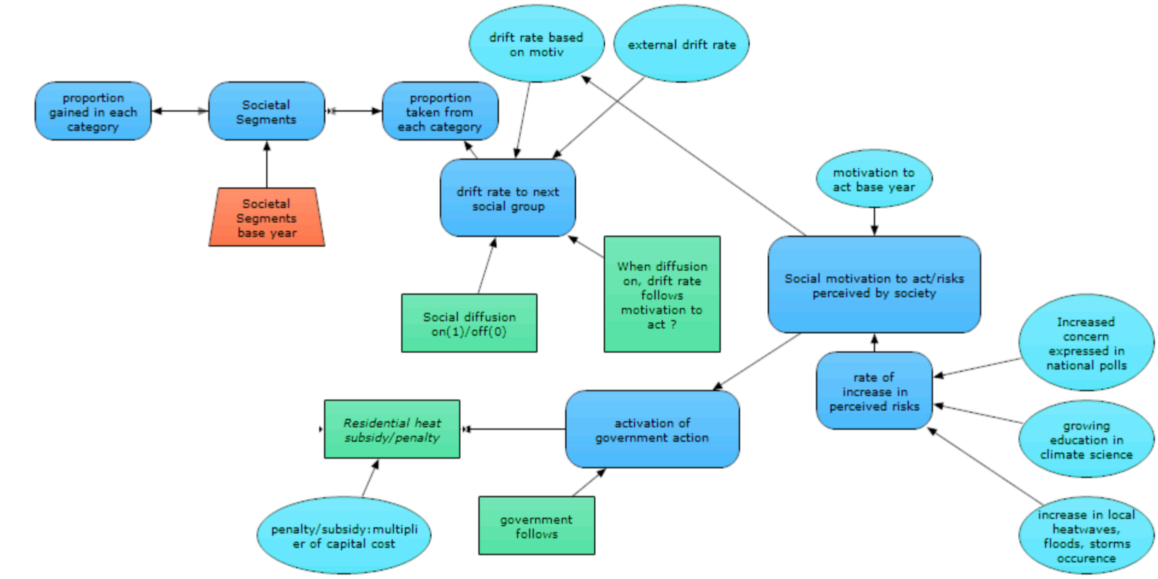
Edit Table of proportion taken from each category

Societal Grouping (Navigate)

very low-carbon ready	0
low-carbon ready	Societal_Segments*(drift_rate_to_next_s/100)
partly low-carbon ready	Societal_Segments*(drift_rate_to_next_s/100)
constrained	Societal_Segments*(drift_rate_to_next_s/100)
very constrained	Societal_Segments*(drift_rate_to_next_s/100)

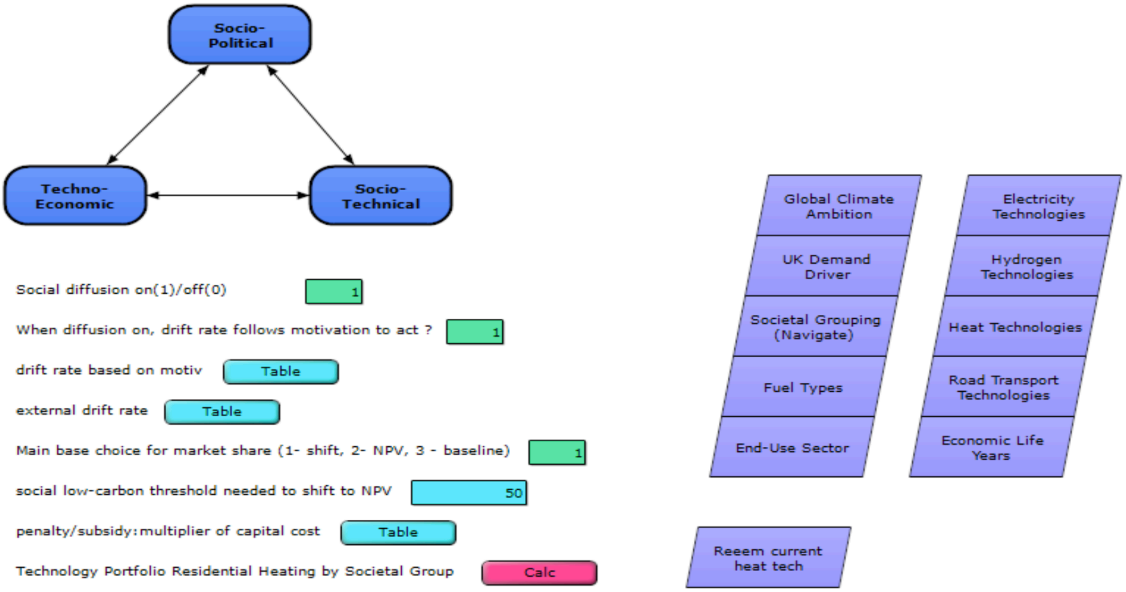
Appendix B: model extension snapshots

Socio-political extension: Environmental diffusion, climate risks perception, and government action:



Socio-technical extension – baseline loop connected to NPV-based choice

Extension's interface



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