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Report on theoretical behavioural framework

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1 Introduction

Much empirical work has been done on the "energy efficiency gap" (Gerarden et al., 2017). Despite the energy efficiency gap has implications for future energy demand projections, it is not well understood in numerical models looking at this issue.

The empirical observations around the underinvestment in energy-efficiency technologies have led to efforts to also include these findings on an analytical and numerical level. Notably, the energy efficiency gap matters not only for ex-post assessment, but also has implications for future energy demand. There have been some efforts to include insight of empirical findings directly, but it is still work in progress and at an early stage.

Future energy demand projections are for example assessed by integrated assessment models and energy system models that analyse long term energy pathways. At the same time, micro-founded economic models based on empirical work are developed. These models might be able to inform the numerical models. In addition, micro-founded economic models could inform welfare functions which could also inform the macro models. Developing analytical tools that can capture these findings in a micro-founded economic model can shed additional light on the findings in the empirical literature: including, sometimes non-linear effects are found, or behaviour is dependent on personal traits or other attributes. While psychology and sociology provide important insights in trying to understand these deep links, taking them into consideration for instance for projections or simulations requires a micro-founded economic model. Once established, such a model allows to simulate the effect of various policies and can inform policy decisions based on the implied outcomes. Moreover, having developed such tools allows to derive welfare measures based on individual's perceived decision, or implicit utility or welfare, which can be aggregated in order to perform a welfare analysis of such different policies. In this report, we propose several frameworks that can be applied in the context of energy efficiency improvements of households and outline how numerical models can be extended to integrate behavioural features including the empirical results from case studies and Randomized Controlled Trials (RCTs) in such models for policy and welfare analyses.

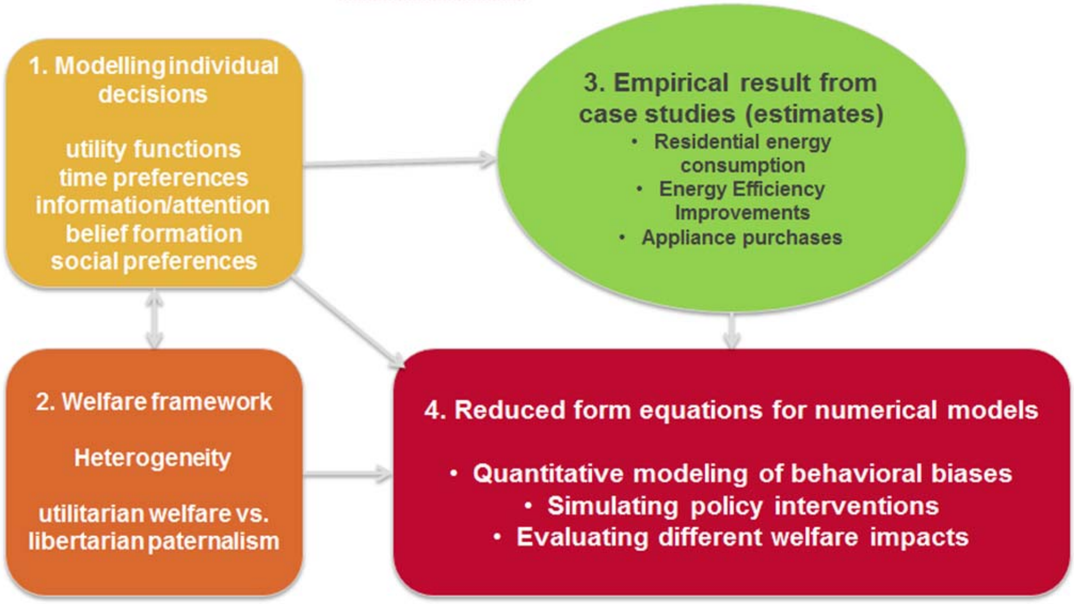


Figure 1: Report structure

Based on these modelling approaches (1), the corresponding and appropriate welfare frameworks can be studied, necessary to quantify the welfare impacts of policies (2). Moreover, these analytical approaches can inform the empirical estimates and results (3). Notably, structural model parameters can be calibrated to coefficients estimated in the econometric models. Ultimately, these three elements can be used in numerical models (4) to better represent behavioural aspects of energy demand and decisions in energy efficiency improvements at the individual/household level.

2 Theoretical frameworks for behavioural biases and features

While psychologists and sociologists have described many behavioural features ore biases[1], in recent years increasingly economic modelling has addressed many of these issues to provide conceptual analysis, microeconomic models deviating from the simple representative rational agent, and notably providing input to numerical models.

Generally speaking, behavioural economics has picked up enormous interest and enriched the discussions by contributing to the now interdisciplinary field of the analysis of human behaviour, where recently including neuro scientists contribute. For a behavioural economist, a classical utility based approach might well explain certain behaviours observed by augmenting the individual's objective (function) he or she maximizes. For instance, the individual might not be aware of all information available to him (limited information) or not perfectly rational when making his choice (bounded rationality). Moreover, preferences might be influenced by others' behaviour or characteristics (for instance, comparing income to others) and thus one's decision affects others and vice versa. More generally, the individual might consider a certain utility or welfare maximization concept while using a different utility when evaluating the decision's consequences.

In order to structure the different biases and behavioural features we consider in theory and practice and which are relevant to energy efficiency concerns, we start by categorizing them into three main categories of biases following loosely (DellaVigna, 2009) and (Allcott and Mullainathan, 2010) including some examples. Overall, they can concern individuals' preferences, beliefs, or decision making rules, see Table 1 based on (DellaVigna, 2009).

[1] Wikipedia currently lists 172 cognitive biases (https://en.wikipedia.org/wiki/List_of_cognitive_biases).

A. Non-standard preferences o **Present-bias** / hyperbolic discounting / self-control o **Reference dependence** / **loss aversion** / endowment effect o Social preferences / **social norms** / altruism
B. Non-standard beliefs o Over-confidence o Law of small numbers (wrongly expect large-sample properties) o Projection bias
C. Non-standard decision making o Framing o Limited attention bias / **Rational inattention** o Suboptimal heuristics o Social pressure o Emotions

Table 1: Overview about three classes of behavioral biases

While several of these behavioural models have been developed, we show the ones that we consider best suitable for the context of energy efficiency and precise framing and motivation of the empirical case studies in progress. A simplified optimization model can frame these different biases which we then explore in the following. This model has been used in (DellaVigna, 2009) and can capture many aspects mentioned above. To fix ideas, the individual's decision program can be written as

$$\max_{x_t^i \epsilon X^i} \sum_{t=0}^{T} \delta^t \sum_{s \in S} p(s_t) U(x_t^i | s_t) \tag{1}$$

In this equation, individual *i* maximizes discounted expected utility over a decision variable x,[2] and where δ is the discount factor and s represents the different states of the world. Let's look at the three cases of non-standard preferences: First, a present bias can be introduced by assuming that the discount factor δ^t is simply

[2] Note that x is not constrained to be a real number but can consist in any set element such as alterative consumption goods, energy efficient alternatives, etc. Moreover, let $y_C(x_t^i)$ denote any characteristic of each alterative, which can be expressed as a numerical value, e.g., costs, annual energy consumption etc.

replaced by a non-exponential discount function $DF(t)$ such as $\beta_{\{t>0\}}\delta^t$ (quasi-hyperbolic discounting as in (Laibson, 1997) or $\frac{1}{1+rt}$ (hyperbolic discounting). Second, reference dependence and such can be represented by adding a reference level r to the utility function: $U(x_t^i, r_t^i\,|s_t)$. Third, social preference emerge when utility depends on the decisions of other people (here referred to as –i, or (possibly)everyone else apart from individual i): $U(x_t^i, x_t^{-i}\,|s_t)$. As far as non-standard beliefs are concerned, they can be represented by a different probability function over the states of the world $p(s_t)$ than the simple probability of each state $p(s_t) = Prob(s_t)$. Finally, non-standard decision making can consist in considering only a subset of alternatives for instance (i.e., a different set definition for X^i) or completely replacing the maximization by a simpler heuristic or other decision method.

Based on applications in the context of energy efficiency, and based on the empirical studies carried out within this project, see Table 2, we focus on five specific biases in the following.[3]

2.1 Present bias

A present bias can arise in a dynamic context, in our case for instance in comparing different appliances or decisions to increase energy efficiency of buildings. The different timing of savings (occurring in the future) and costs (occurring in the present) can lead to a present bias, when present costs are overvalued against future cost-savings. Consider investment costs of alternatives x, I_x^0 , and running (for simplification) constant annual costs c_x. This implies a utility function specification for each alternative x simply given as

$$U(x_t^i|s_t) = \begin{cases} -I_x^0 \; for\; t = 0 \\ -c_x \; for\; t > 0 \end{cases}$$

The main program (similar to the discussion about the implicit discount rate in (Schleich et al., 2016)) can then be simplified to

[3] These are also indicated in bold in Table 1.

$$\max_{x_t^i \epsilon X^i} -I_x^0 - \beta \sum_{t=1}^{T} \delta^t c_x$$

If $\beta = 1$, discounting is exponential and preferences are time consistent, while for $\beta < 1$, a present-bias is present and implemented as quasi-hyperbolic preferences. Based on this simple illustration, we can show how a present-bias can be interpreted as an implicit perceived running cost (a recurrent energy or other expenditures) vs. initial investment costs in, for instance, light bulbs or other appliances. For a simple one-period model, we can compute the perceived costs $\widehat{c_x}$. Realizing that $\sum_{t=1}^{T} \delta^t = \delta \frac{1-\delta^T}{1-\delta}$, we can rewrite this program as

$$\max_{x_t^i \epsilon X^i} -I_x^0 - \delta \frac{1-\delta^T}{1-\delta} \widehat{c_x}$$

where $\widehat{c_x} \equiv c_x/\beta$ is the (higher) perceived future costs compared to today's investment decision. That is, in a numerical model, adjusting future costs by this factor allows to take implicit a present-bias into account without changing the model's optimization program.

2.2 Status-quo bias

Status-quo bias plays a potentially important role, linked to the previous and next biases. However, it links the status quo to the decision problem thus biasing any decision over the current status.[4] In a simple way, one can consider prevalence of a given decision based on the available options $x_t^i \epsilon X^i$ such that until a time T, the status-quo cannot be changed: $X_t^i = \{x_0^i, t < T; X^i, t > T\}$. That is, requiring the agent to not change the decision until T will result in persistence. In a more gradual fashion, an adjustment cost function *adj(x)* in a distance measure in an attribute of each alternative $y_C(x_t^i)$ can be considered in the utility function as

$$\max_{x_t^i \epsilon X^i} \sum_{t=0}^{T} \delta^t \underbrace{U(x_t^i) - adj(\|y_C(x_t^i) - y_C(x_0^i)\|)}_{\widehat{U}(x_t^i)}$$

[4] The status quo bias can be linked to other biases including loss aversion and reference dependence and be framed in a similar fashion, see Masatlioglu and Uler (2013).

2.3 Loss aversion

While in the standard case, losses and gains are equally weighted in the utility function, empirical studies generally find having different slopes and curvatures of the utility function from gains and losses have been found in empirical studies (Kahneman and Thaler, 2006). Notably, risks about losses seem to be more penalized penalizing than gains.

$$\max_{x_t^i \epsilon X^i} \sum_{t=0}^{T} \delta^t \sum_{s \in S} p(s_t)\left[U\left(x_t^i \middle| s_t, y_C(x_t^i\right) > y_C(Ex_t^i) + V\left(x_t^i \middle| s_t, y_C(x_t^i\right) < y_C(Ex_t^i)\right]$$

Here, two different utility functions capture losses and gains (compared to the expected value $y_C(Ex_t^i)$ in any characteristic of the options (e.g., future monthly energy prices).

2.4 Rational inattention

Rational inattention can take a form similar to the previous two biases, but allows for a framing in different directions. It can concern different attributes of a certain consumption option, not limited to costs or the status quo. Assuming limited attention means that individuals do not use all the available information but simplify complex decisions, for example by processing only a subset of information. For example, consumers might underweight certain aspects, typically those that are less salient. DellaVigna (2009) models this by implementing an inattention parameter θ that is decreasing in the salience s. Due to inattention the consumer perceives the value of a good to be $\hat{V} = v + (1 - \theta)o$, where θ denotes the degree of inattention, with $\theta = 0$ being the standard case of full attention. The interpretation of θ is that each individual sees the opaque information o, but then processes it only partially, to the degree θ. Sallee (2014) develops a set of conditions under which consumers tend to be rationally inattentive to energy costs, which is particularly likely if consumers have strong preferences concerning other product features. When choices are driven by misperceived product attributes, consumers are making decisions, which reduce their experienced welfare. Consumers that misperceive product costs for example do not maximize experienced utility but decision utility. When systematically biased, choices can potentially be corrected through information disclosure (Allcott, 2013).

2.5 Social norms

Social norms are about guidelines and implicit rules regarding what is common or desirable within a group or a society at large (Cialdini and Trost, 1998). In terms of microeconomic founded models, (Bénabou and Tirole, 2011a) provide a model, where prosocial behaviour can emerge by considering a social multiplier (social norms such as honour or stigma) in the utility function. The very general utility function taking into account intrinsic motivation v, extrinsic motivation y, the cost of contributing c, is augmented by the externality e of the average of action $\bar{a} = E[a]$ in the population and a weight μ of one's care about the societal norm. The latter is simply the posterior expectation of the intrinsic motivation v thus given as $E[v|a]$ and the utility function is written as $U = (v + y - c)a + e\bar{a} + \mu E[v|a]$.

Here the intrinsic motivation (or prosocial valuation) v (similar to rho in the previous section) is private information and cooperation reveals some information about its distribution $G(v)$ in the population. The optimal strategy in this framework is to contribute (a=1) only if one's intrinsic pro-social value v exceeds a certain threshold v^* and do not contribute (a=0) for any set of external costs and benefits. Fairly simple comparative statics can be obtained with respect to the parameters of the model. A crucial result is the endogenous bifurcation of the actions as considered by individuals. If v^* is low, little is learnt from prosocial behaviour (considered as only "respectable") compared to when v^* is high or considered as "heroic". Differences in μ or the value one places to social esteem could be interesting and matched with elicited participant's preferences.

Spill-overs in the case of more than one action could be also studied in this framework (e.g., residential energy savings and transportation, …). Different specifications are possible and could be explored for the experiment consisting in different direct incentives $y_{a,b}$ and social sanctions/rewards $\mu_{a,b}$, with one being set to zero in either of the two domains. Combining both actions and utilities, the fundamental change in the utility function would consist in the social norm which now would read $[v_1 + v_2|a_1, a_2]$. In this case, the optimal thresholds v^* depend on both actions due to the inference drawn from the other action, if there is a signaling value across domains $f(v_1|a_2) \neq f(v_1)$ (similar to equation (24) in (Bénabou and Tirole, 2011a)). In particular, positive spill-overs occur if both actions are positively related. Within this framework, welfare results can be easily obtained and depend on where v^* is located in both tasks/actions (heroic (high) or respectable (low)).

As an alternative, a social norm can also play a role if individual behaviour by the social group through self-inference, as in the model by Bénabou and Tirole, (2011b) predicts. Here, there is no direct influence by others at all but rather the individual's actions signalling to herself information about her characteristics $\in \{v_l, v_h\}$. The process of self-inference works as follow: first people form a belief of what kind of persons they are (the key parameter is ρ, the probability or weight of being a highly altruistic person). Then they remember their true valuation with probability (λ) and with (1-λ) they no longer recall it and use the past choices to infer the type of person they are. Different priors ρ and investments x in one's self-view can thus lead to history-dependent behaviour. The fundamental result of the model is a hump-shaped curve of the initial prior on the personality ρ (which characterizes the likelihood of being "moral", i.e., $v = \rho v_h + (1-\rho)v_l$, e.g., in terms of prosocial behavior) for the choice to act pro-socially (x). In particular, predictions entail that contribution or pro-social action increases for a lower cost of contributing, more salience of the perceived self-inferred value, less "remembering", while it has a hill-shaped relationship with the initial prior. The key prediction is thus the non-monotonic, inverted U, relation between investments in morality and the probability or weight of being an altruistic person (ρ). When the prior of being altruistic is low it doesn't make sense to invest in self reputation, and similarly it is not needed when it is already high. Note that spill-overs can easily arise in this model: people are motivated to engage in moral investments for a variety of motives (self-esteem, anticipatory utility, self-control). The key in the model is informational: people are unsure of their deep preferences, so there is an information gap to the reasons why previous moral choices were undertaken. This model thus allows to reconcile two opposing results from the experimental literature: when one acquires moral credentials (ρ becomes sufficiently high) then he or she is licensed to act immorally afterwards, as evidenced in (Mazar and Zhong, 2010; Monin and Miller, 2001). If instead the investment changes weaker aspects of identity (ρ changes marginally, and is not too high or too low) this has confirmatory responses, as in the 'foot in the door' effect. Thus, the first and second cases correspond to negative and positive spill-overs respectively. Relatedly, there is empirical evidence from social psychology on moral crediting versus salience of identity, but the evidence is mixed. Mazar and Zhong (2010) show that if people are merely exposed to green goods, then they behave more altruistically. But if they actually purchase green goods, then they become less altruistic, and also more immoral. The first results could be attributed to an increase in salience, and the second to a large increase in ρ. Van der Werff et al. (2014) show that reminding people of their past environmental behavior influences environmental self-identity, which is in turn positively related to subsequent environmental judgments and intentions. Schnall et al. (2010) show that witnessing another person's altruistic behavior elicits elevation, a discrete emotion that, in turn, leads to tangible increases in altruism. On the other hand, (Eskine, 2013; Sachdeva et al., 2009) find the opposite: affirming moral identity leads to subsequent moral licensing. Allcott and Rogers (2014) observe the 'action and backsliding' effect, which could be both interpreted as a salience effect and a moral licensing.

3 Welfare frameworks in the presence of behavioural biases

Since the inclusion of such behavioural biases into economic models is not obvious, in particular if the behavioural features underlying individual's decisions and perceptions or welfare are unknown, Chetty (2015) argue that three potential tools can be used to analyse their impact. Firstly, measures of subjective well-being or happiness can be used as an overall measure including all relevant psychological and social factors. Secondly, by observing decisions where we can "trust" agents' choices as reflecting their true experienced utility, we can derive a "sufficient statistic" for inferring the true experienced utility of individuals. Thirdly, using a structural model incorporating explicitly certain behavioural features allows to identify and quantify the impact of individual behaviour.

Indeed, when assessing the welfare impacts of behavioural biases and public policy interventions such as nudges and others, different welfare concepts can be employed (Bernheim, 2009; Bernheim and Rangel, 2009). One notable application for the context of energy efficiency improvement policies can be found in Heutel (2015). Important concepts in welfare comparison include the differentiation between utilitarian individual welfare vs. libertarian paternalism (Thaler and Sunstein, 2003).[5]

In practical terms, the "accounting approach" of welfare measurement counts the monetary costs and benefits, plus uninternalized externality benefits of any policy. This approach is widely used for the evaluation of most energy efficiency programs, because it is not very informationally demanding (Allcott and Greenstone, 2017). It has a limitation though, as it does not allow to evaluate counterfactual policy structures. The "revealed preference approach" on the other hand involves using observed decisions to estimate utility function parameters. To identify this effect, one needs exogenous variation in prices or subsidies to identify the slopes of different demand functions. A randomized experiment helps to solve these problems.

In the presence of behavioural biases, welfare evaluation becomes less trivial: not only are externality reductions to be factored in, but also potential "internality" reductions (Allcott and Taubinsky, 2015).

Having discussed the different welfare frameworks and concepts that can be applied, we can consider and evaluate different policies in this context. We discuss

[5] More details on welfare frameworks to be added once the particular models and biases implemented are defined.

different policy interventions, which can also address sub-optimal decisions, and thus help to overcome limits to improving energy efficiency. Frederiks et al. (2015) summarize the biases and potential policy options in the context of energy efficiency savings.

Three broad categories can be distinguished including

1. Regulatory standards
2. Financial incentives
3. Informational instruments

While the first two sets comprise standard economic instruments, the third category comprises tools such as default options, types of commitment devices, audits and labels, information about others, or general informational campaigns, and persuasion strategies ("nudges") of different types. These tools are in particular important in the presence of several of the biases discussed above DellaVigna (2009) and Allcott and Mullainathan (2010). Once the bias is implemented in the model, we can add the policy lever on top and evaluate both the effectiveness (in terms of energy efficiency improvement) and welfare outcome (according to the different welfare concepts outlined above) of different policies of the three categories.

4 Linking with empirical results and parameter estimates

Based on the microeconomic models applied to energy efficiency improvements, we can identify economic parameters that can be included also from numerical results and calibrate based on empirical estimates. A methodological requirement is thus a close tie between the behavioural model and the field experiment ("*structural behavioural economics*"), allowing for structural estimation of the underlying parameters (DellaVigna et al., 2012). Of all field experiments published in top five journals until 2010, only two papers have this feature, see for an overview Card et al. (2011). Few papers have looked at estimating discounting functions, or a projection bias for catalogue orders structurally estimated (Conlin et al., 2007). More recent examples in the context of energy efficiency include Allcott and Taubinsky (2015) and Tsvetanov and Segerson (2013).

Based on the analytical model outlined in section 1, we can identify parameters and model features that can use empirical estimates to calibrate these models. Firstly, in order to determine the precise model and feature relevant to our analysis, we consider the various empirical cases studied within the PENNY project, which provide novel estimations of individual behaviour in energy efficiency of households. As for the behavioural biases discussed above, five of them have been analysed empirically within PENNY. These are summarized in the following short table:

Table 2: Empirical case studies in the PENNY project

Institution	Research Question	Type of bias /behavioral feature
RUG	Does tariff differentiation stimulate customers to shift their energy use in time? Is tariff differentiation combined with an environmental appeal more effective? What are the effects on spill-over behaviors?	Inattention bias
WWU	Can goal setting reduce time inconsistent behavior and thereby contribute to a lower consumption of energy by households?	Present bias (Social norms) Reference dependence (Information asymmetry)
ETH Zurich	Can energy and investment education increase the ability of households to take optimal decisions with respect to the purchase of electrical appliances?	Sub-optimal heuristics Inattention bias
ETH Zurich	What is the role of full information disclosure in the adoption of energy efficient appliances? Can the minimization of cognitive effort to evaluate different appliance options increase the adoption of energy efficient appliances?	Sub-optimal heuristics Inattention bias Bounded rationality
ETH Zurich	What is the role of loss and risk aversion in the adoption of energy-consuming durables?	Reference dependence Status-quo bias
FEEM	What is the impact of social cohesion, social identity and homogeneity on the effect of social information?	Social pressure Social norms
FEEM	What is the impact of salience of energy costs on purchase of EE appliances?	Rational inattention Present bias
FEEM	What is the relative impact of monetary information, environmental information and of their combination on EE purchases?	Rational inattention Present bias

The actual information of empirical parameter estimates and uncertainty ranges, including heterogeneity across countries and individuals, will be used to inform the modelling. The actual data exchanged will be evaluated and implemented once the empirical estimates are available throughout the project.

5 Approaches to integrate empirical results in numerical models (WP4)

Based on the microeconomic model, equations suitable for energy system models (ESM), Computable General Equilibrium (CGE) or integrated assessment models (IAM) can be implemented (examples include the equations discussed above, such as disutility costs, hyperbolic discount rates, social influence effects, investment hurdle rates). Moreover, the empirical parameters informing the microeconomic models will allow to calibrate these models numerically. Finally, the impact in terms of energy efficiency gains, economic costs, difference from the first best, and policy costs can be computed using these models. The evaluation of different definitions of welfare based on the model outcomes will provide guidance as to how important the biases are from a societal or individual welfare perspective. In fact, the review by Hughes and Strachan (2010) found that only very few scenarios take social aspects into account, none with political aspects, and that scenarios with social aspects contain little or no detail on economic and energy aspects.

Calibration of preferences and heterogeneity at the individual and country level provides another important data requirement for the consideration of these effects. In particular, data at the individual and country level of social, risk, time, and moral preferences can shed a light on these effects in different contexts, see for example the data collected in Falk et al. (2017).

Models in PENNY	WITCH	EDGE	WIOD-CGE	MUSE[6]
Model type	IAM	IAM	CGE	ABM
Time horizon	100 years, 5 years step	100 years, 5 years step	1 year, static	XX years, 30 time slices
Regional aggregation	17 world regions	11 world regions	3-40 regions	1-30 regions
Sectoral focus	Supply side	Buildings	Supply & Demand	Industry & Buildings

Table 3: Numerical models within the PENNY project

[6] MUSE is used in a related EC project (COBHAM) with a similar focus.

5.0 Energy System Models (ESM)

Among the widely used energy system models, there are some complex models that allow to represent detailed energy end use, in particular for the building sector, aiming at projecting future energy consumption. Examples of models that do contain this detail are MARKAL/TIMES, NEMS, LEAP, and PRIMES.

5.1 Integrated Assessment Models (IAM)

Large scale integrated assessment models (IAM) typically combine a model of the macro economy with an energy system (among others), and thus inform the decision about energy demand to various degrees. In terms of solution method, simulation and intertemporal optimization models can be mainly distinguished.

The IMAGE model (Stehfest et al., 2014) is one example of a simulation model, where decisions on energy and technology services are based on relative costs of the ensemble of choices using a multinomial logit approach.

In the intertemporal optimization model WITCH (Emmerling et al., 2016), on the other hand, the representative agent in each region maximizes discounted utility of consumption, which itself is derived from Energy Services (ES) and other sectors/goods. Output is generated through a nested CES function:

$$W(n) = \sum_t l(t,n) \frac{\left(\frac{C(t,n)}{l(t,n)}\right)^{1-\eta} - 1}{1-\eta} \beta^t$$

$$Y(t,n) = \frac{tfp0(n)\left(\alpha(n)\left(tfpy(t,n)K_{FG}(t,n)^{\beta(n)}l(t,n)^{(1-\beta(n))}\right)^{\rho} + (1-\alpha(n))ES^{\rho}(t,n)\right)^{\frac{1}{\rho}}}{\Omega(t,n)}$$

Hence, model parameters capturing trade-offs at the energy consumption and intertemporal level are the discount factor β, the substitution elasticity between ES and other goods $\sigma = \frac{1}{1-\rho}$, and he factor shares $\alpha(n)$ which are also region-specific.

The demand sector representation is in some IAMs more detailed than in others, specifying for example the specific energy end uses and technologies, as in the IMAGE model discussed above. Technology choice generally depends on cost considerations. However, stylized sub-optimal choices are as well represented in the model, through calibration and hurdle factors, as well as using logit distributions. In the multinomial logit equation the lambda (λ) determines how sensitive the distribution of market shares are to price differences of different technology options (i), which can be calibrated to observed market heterogeneity.

$$\mathrm{MarketShare}_{i,t} = \frac{\exp\left(\lambda \cdot \mathrm{Cost}_{i,t}\right)}{\sum_i \exp\left(\lambda \cdot \mathrm{Cost}_{i,t}\right)}$$

In this equation, λ is the so-called logit parameter, determining the sensitivity of markets to price differences. The equation takes into account direct production costs and also energy and carbon taxes and premium values. The last two reflect non-price factors determining market shares, such as preferences, environmental policies, infrastructure (or the lack of infrastructure) and strategic considerations. The premium values are determined in the model through a calibration process in order to correctly simulate historical market shares on the basis of simulated price information. The same parameters are used in scenarios to simulate the assumption on societal preferences for clean and/or convenient fuels. However, the market shares of traditional biomass and secondary heat are determined by exogenous scenario parameters (except for the residential sector discussed below). Non-energy use of energy carriers is modelled on the basis of exogenously assumed intensity of representative non-energy uses (chemicals) and on a price-driven competition between the various energy carriers (Daioglou et al., 2014; Stehfest et al., 2014).

More recently, there has been some effort in explicitly including behavioural considerations in vehicle choice distinguishing between different types of users. McCollum, D., et al. (2017) developed a method to include heterogeneous consumer preferences for non-financial attributes of alternative fuelled vehicles (AFVs). These attributes include range anxiety, refuelling station availability, risk, diversity of vehicles on offer and the electric vehicle charger installation. In a multi-model comparison they find that when these attributes are considered, the sectoral policies explicitly targeting consumer preferences have to enable widespread adoption of alternative fuelled vehicles, in order to interest also more reluctant consumers. In a separate study, Pettifor et al. (2017) draw on empirical data to quantify risk aversion to alternative vehicles. In this case an aggregated risk premium value is calculated based on a synthesis of discrete choice studies measuring stated preferences for AFVs. To calculate mean risk premium and standard deviation risk premium, the willingness to pay ratios for AFVs are assumed normally distributed. Building further on Roger S-shaped adopter curve, this distribution is translated to the risk premiums for different consumer groups.

Finally, a similar approach to modelling energy demand again in the residential buildings sector related to the PENNY project is the EDGE model linked to the ReMIND model (Bauer et al., 2013). The EDGE model considers final energy demand for four activities in the buildings sector:

1. Cooking
2. Water Heating
3. Space Cooling
4. Space Heating
5. Appliances and Light

The activities are driven by socio-economic and climatic drivers, take into account floor space demand, and are satisfied by different energy carriers and energy efficiencies. Energy demand is computed based on income elasticities, Gompertz functions calibrated on past data to replicate S-shaped penetration curves, and functions to reflect changes in climatic variables notable for cooling and heating (Levesque et al. 2018). In this formulations, quasi-cost parameters can be introduced to reflect behavioural biases once the econometric estimates of different energy efficiency saving options or decisions on appliances are known. The relatively simple structure will allow to implement such biases in this model relatively easily, and will be executed in the modelling application of PENNY.

5.2 Agent-Based simulation Models (ABM)

The numerical complications for large-scale general equilibrium or optimization models and possible lack of behavioural realism have led to a strand of numerical models that derive the macro picture starting from individual behaviour. These models start from individual objectives, modelling individual and heterogeneous agents. Such Agent Based Models (ABMs) thus allow to consider a variety of heuristics, objectives of individuals, capturing heterogeneity. However, achieving consistency across the economy can sometimes prove to be difficult. In particular several ABMs have been used for the electricity market, see Sensfuß et al. (2007) for an overview. MATISSE-KK (Köhler et al., 2009) is an example of an ABM focusing on the transport sector that includes changing regimes in mobility and niches and dynamic transitions within these systems.

Another model applied to residential energy demand, and thus relevant in our context, is MUSE[7] (ModUlar energy systems Simulation Environment, see Sachs et al. (2017)), which has been developed in this realm to capture consumer behavior and heterogeneity to a greater extent (Henry and Rai, 2016; Pfenninger et al., 2014). It models six end-uses (Water heating, lighting, space cooling, space, heating, cooking, appliances (computer, fridge, freezer, washing machine,...), 48 technologies, and 30 time slices. In this model, consumer demand side aspects are captured through three main channels:

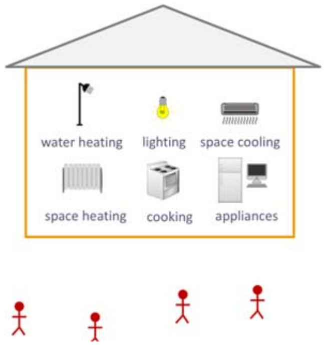


Figura 1: Energy end uses in MUSE (Source: Sachs et al. 2017)

1. Objectives (economic, environmental, comfort, ...)
2. Search space (all alternatives, close to existing, popular, mature alternatives)
3. Decision strategies (Single objective, weighted sum, additional constraints, lexicographic)

And these dimensions are moreover all distributed so to take into account personal and household

4. Heterogeneity (type and percentage in the population, e.g., Sinus Milieus)

Demand here is determined relatively simple from baseline drivers via a logistic function:

[7] http://www.sustainablegasinstitute.org/home/muse-energy-model/

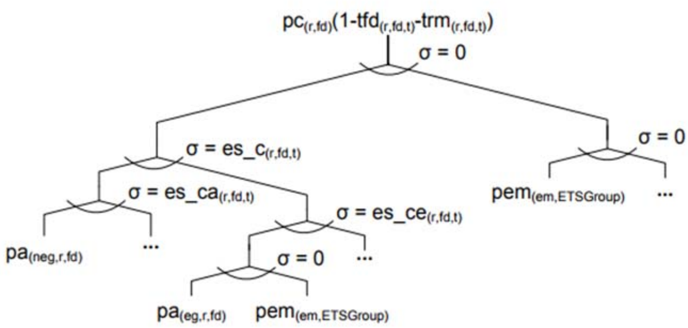
Determine parameters a, b, and c for logistic function

$$Demand = \frac{a}{1 + be^{c * GDP}}$$

In terms of the general model of behavioral features, the points 1.-3 are easily reproducible by adjusting the maximization program in equation (1). Indeed, this modeling approach is particularly suited to consider different decision rules, alternative welfare criteria, and heuristics. It can thus represent the biases in all categories A, B, C categorized in Table 1. Notably, as with non-standard decision making criteria, it provides the easiest framework for these features. A key feature of ABMs is that interactions between agents can be included. Social norms for example is a behavioral feature that depends on the preferences of the other agents. By modelling this dynamically possible shifts in social norms could be observed.

5.3 Computable General Equilibrium models (CGE)

CGE models including energy sector representation have been another set of models looking into energy demand related effects on the economy. A multi-sector economy in a static or recursive-dynamic setting with a representative household and firm allows to solve for the full market equilibrium across sectors. WIOD-CGE (Koesler and Pothen, 2013) is an example of such a CGE model. It covers about 35 sectors, three macro regions with a focus on Germany and the EU, and a household maximizing utility aggregated through a CES function from goods of all sectors including energy services, which itself is obtained combining machinery and electricity flows as inputs.



Given the static nature of this model, in particular as for the present bias, and implementation based on different discount rate is not feasible directly. However, systematic biased beliefs about energy costs that are for example caused by inattention can be modeled by implementing these misperceived energy costs in the representative households decision making process. As we showed under 2.1, a present bias can be modelled simply by adjusting the costs of future energy bills adjusting them by empirically calibrated discount factors β.

6 Conclusion

The increasing empirical work on estimating individual behaviour including behavioural biases as led to a better understanding of the magnitude of such effects for individual consumption decisions. Yet, in order to implement such factors in numerical models to analyse the effect e.g., in the context of energy demand projections, one needs to use mathematical models representing such factors, and welfare framework to evaluate different scenarios. This will be the next step towards implementation and modelling within the PENNY project based on the frameworks outlined in this report.

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