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Scenarios and analysis of policy interactions in the EU

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Scenarios and analysis of policy interactions in the EU

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Table of Contents

Executive Summary

Building on the models developed in D4.1, we further improve these models and run simulations to analyse long-term scenarios of energy consumption. To accomplish that, we improve the empirical grounding of behavioural features in the global ABM model MUSE in the first part of this report using the data that was collected in the PENNY project. The combination of the actual electricity consumption data with user characteristics provides the opportunity to relate agent typologies with energy consumption response. For each agent the energy service demand is estimated, to distinguish between lifestyle and energy efficiency effects. Based on cluster analysis methods we were able to partition a large population into groups with pretty strong demand-related characteristics, which formed the basis for deeper investigation into socio-demographical backgrounds, consumption and investment behaviour. In the second part of this report, the infrastructure topic is addressed. For this purpose the existing global buildings model EDGE has been further developed. It has been extended with a building stock and insulation investments module, in order to include the representation of the development over time of building vintages affecting potential of building envelope energy efficiency enhancements. Improved understanding of final energy demand developments across different world regions was reached by involving building stock dynamics in the computation. In the third part, this report extends the analysis of households' energy service consumption by simulating electricity price misperceptions and behavioural inefficiencies in the WIOD CGE model. In this part, we conclude that the impact of potential policies aimed at increasing households' energy efficiency will crucially depend on whether households actually observe prices in an unbiased fashion. Our simulations further indicate that households' ability to process information and modify their expenditure structure accordingly is a decisive factor for the success of efficiency improvements in their homes.

Summary for Policymakers

By further developing a number of models -including agent-based, integrated assessment and computable general equilibrium (CGE) models - we were able to incorporate the empirical findings of PENNY and explicitly take into account behavioural shortcomings in energy service consumption and residential energy use. Using the CGE model, long-term energy consumption scenarios in the presence of behavioural shortcomings were simulated. The central aim of the CGE model scenarios is to analyse the impact of misperceived energy prices in energy service consumption on the consumer demand, the associated impact on production sectors in Germany and Europe and CO2 emissions.

We conclude that the impact of potential measures to improve the energy efficiency of households' will depend to a large extend on whether households actually observe prices in an unbiased fashion. The simulations further indicate that households' ability to process information and modify their expenditure structure accordingly is a decisive factor for the success of efficiency improvements in their homes.

We find that misperceived electricity prices change the way energy services are consumed and the associated energy efficiency, but do not significantly affect the overall consumption of these services. With respect to the rest of the economy in Germany and the EU, changes in industrial production as well as private consumption remain rather small for those goods that are only indirectly affected by the misperception of electricity prices, which is because the market price of electricity does not change much.

Providing information on electricity prices can have a positive effect on electricity demand reductions if households are able to identify possible trade-offs in their energy service consumption. Households that are aware of alternative and more

efficient electric appliances can reduce electricity consumption by switching to more efficient technologies.

We further demonstrate, that improving the knowledge on how to save energy using appliances more efficiently has a greater effect in the short-run. If households are able to adjust their behavioural efficiency in energy service consumption over the long term they might refrain from buying more energy efficient technologies. As the electricity sector is mostly affected by the price misperceptions and behavioural inefficiencies of households, electricity production levels and CO2 emissions are also higher if prices are perceived to be lower than they actually are.

However, when consumers perceive the electricity price to be higher than it actually is, providing actual cost information can turn out to be counterproductive in terms of energy demand reductions and CO2 emissions as households might realize that they pay less than they expected. Therefore, from a private perspective, households might invest too much in energy efficiency, but from an environmental point of view this over-investment could be beneficial. Potential co-benefits that result from reduced energy demand like health benefits through better air quality will have an additional effect on welfare.

The model based assessment emphasise the crucial role of promoting energy efficiency, both in terms of behavioural change than of investments and innovation. Achieving low carbon targets in a low energy demand system is much easier economically and socially: it limits the amount of investment needs, limits the increase of energy prices and bills, and also provides important economic and social co-benefits such as for increased air quality.

1. Introduction

Mitigating greenhouse gas emissions in households, the industry and buildings' sectors require users to make different choices. While the potential for demand side changes is substantial (Grubler et al. 2018), and possibly economically viable, these changes depend also on preferences related to behavioural and social factors. As presented in the literature overview of the project, economists describe many behavioural features or biases in consumer choice towards more efficient energy services. Economic modelling has increasingly been used to address many of these issues by providing a conceptual analysis and microeconomic models that deviate from the simple representative rational agent, and notably providing input to numerical models. The primary aim of the PENNY project is to better understand the psychological, economic and social barriers that influence energy efficiency in households, the buildings and industry sector. In this deliverable the impact of these barriers in long-term energy projection and the role of energy efficiency policies are assessed.

Increasing energy efficiency has been identified to be one of the central objectives in the transition processes towards low-carbon economies globally. The European Union aims to improve energy efficiency by at least 27% for the year 2030, compared to projections of future energy consumption. As residential consumption accounts for about 25% of the total final energy consumption in the EU-28 region in 2016 Eurostat (2017), making up a non-negligible share of about 5% of total household consumption expenditure, consumers are expected to take a more active and central role in the energy markets of the future. Overall, the buildings sector accounts for around one third of the total global final energy use and one half of the total electricity, which is linked to 20% of energy-related greenhouse gases emissions (Urge-Vorsatz et al. 2013)(OECD 2013). Energy consumption development is driven by many factors, ranging from population increase, reduced household size and rising affluence, which cause increasing demands for improved thermal comfort and a wide variety of electricity-based services. At a global level, buildings Final Energy Demand (FED) is expected to increase by 50% by 2050 if current trends are followed (OECD 2013). By contrast, there is a wide consensus that future final energy use in buildings may stay constant or even decline by mid-century, if today's cost-effective best practices and technologies are diffused (Urge-Vorsatz et al. 2013), with 40 exajoules that are estimated to be possibly saved in 2050 in the buildings sector through the wide deployment of best available technologies (Urge-Vorsatz et al. 2013).

The energy consumption characteristics of the building sector are complex and inter-related (Swan and Ugursal 2009). Within the buildings sector, very long lifespans of buildings and retrofits lead to a very significant lock-in risk, resulting in inertia for policies energy efficiency. At the same time, there is a strong path dependency of choice made now for the future efficiency potential, pointing to the urgency of ambitious and immediate measures. While in OECD regions, approximately 75% of the current building stock will be still standing in 2050, income growth in developing nations is expected to drive high new construction rates (OECD 2013). Hence, renovation of the current building stock should be made a priority in the former countries, while the most important need in the latter regions is related to urgent enforcement of stringent building codes for new buildings. Therefore, when analysing long-term climate mitigation strategies, a thorough understanding of the building stock dynamics is required.

Integrated assessment models have been used extensively by policymakers and global assessments to evaluate consistent pathways of climate change mitigation (Tavoni et al. 2015). However, while in IAMs projected pathways, energy efficiency in buildings plays an important role to meet set climate targets, the complexity of building infrastructure is generally neglected. In a similar manner, the complexity of behaviour heterogeneity in energy choice, which can feature non-linear relationships, interactions, path dependence is difficult to capture in these long term models (McCollum et al. 2017). The broad scope of the models means that the interest lies in understanding the aggregated trends which does not match with the complexity of these features (Krey 2014).

Not including behavioural heterogeneity and infrastructure dynamics in the building sector projections can lead to several issues: 1) Potential for energy demand reduction can be overestimated or underestimated. Possibly certain perceived hurdles or attraction factors could result in different levels of demand side changes; 2) Characteristics that are associated with technology or societal transitions, such as feedback effects, path dependencies are not captured; 3) Behaviour related policies cannot be evaluated directly, such as information campaigns or targeted fiscal initiatives.

Two innovative modelling methods have been developed that address two key issues affecting energy efficiency pathways in the building sector: 1) heterogeneity of the energy efficiency choices, 2) inertia in an energy efficiency transition due to the slow turnover of the building stock. Using the inputs from previous work packages, we are able to improve the representation of consumer behaviour and investment decisions for energy efficient goods in these models.

Furthermore, based on the CGE model developed in Task 4.1, we simulate long-term energy consumption scenarios in the presence of behavioural shortcomings. The central aim of the CGE model scenarios is to analyse the impact of misperceived energy prices in energy service consumption on the consumer demand, the associated impact on production sectors in Germany and Europe and CO2 emissions. We make use of a CGE model to take into account endogenous price changes and the linkages between regions and markets. This allows us to analyse regional and global demand and supply effects and show how this behavioural bias affects consumption and welfare.

2. Improving energy efficiency dynamics

Recognizing however how important it is to assess the role of heterogeneous behaviour to evaluate policy affecting emergent phenomena, in the first part of this deliverable we take the challenge to improve the empirical grounding of behavioural features in the global ABM model MUSE (Sachs et al. 2019). In order to do so we start with the data, which was collected in the PENNY project and further extended with data collected during the Cobham project.[1] This data is based on household survey data from 3 European countries combined with metered electricity consumption data, to analyse how heterogeneity in the socio-demographic characteristics, dwelling typologies and the attitudes of residential energy users affects the way in which these users make and implement decisions to improve the energy efficiency of their home. The combination of the *actual* electricity consumption data with the user characteristics provides the opportunity to relate agent typologies with energy consumption response. For each agent the energy service demand is estimated, to distinguish between lifestyle and energy efficiency effects.

In the second part of this deliverable, the infrastructure topic is addressed. For this purpose the existing global buildings model EDGE has been further developed (Levesque et al. 2018). The model can be defined as a bottom-up, statistically based simulation model, which is multi-regional and employs a long-term point of view. It has been extended with a building stock and insulation investments module, in order to include the representation of the development over time of building vintages affecting potential of building envelope energy efficiency improvements.

The scope of the analysis is the European buildings sector. Energy use in domestic buildings accounts for approx. 25% of the EU's total final energy consumption (EC 2018) and has been the focus of numerous policies and programmes to reduce residential sector emissions, such as the Energy Labelling Directive and the Energy Performance of Buildings Directive. The building stock analysis in addition examines the role of European building envelope policies within the global context, showing different stock dynamics in developing compared to the developed countries. Research efforts to better understand drivers of consumer decision-making, going beyond the evaluation of the technical potential, is central to delivering these policies and programmes.

[1] http://www.cobham-erc.eu/project/

2.1 Improved agents representation in the MUSE agent based model

Rai & Henry (2016) argue that Agent Based Models (ABM) are a powerful tool to represent *energy choice* and capture the uniqueness of individuals and interactions between them to better understand the overall system dynamics (An 2012). Following the Farmer & Foley (2009) definition, ABMs are "computerized simulation of a number of decision-makers (agents) and institutions, which interact through prescribed rules". Rai & Robinson (2015) point out that ABMs face two important challenges: Often behavioral decision rules applied in the models are introduced in an ad hoc fashion, which makes it difficult to understand the implication of behavioural factors in a broader context (theoretical challenge) (Durlauf 2012). Second, there is a lack of empirical data to appropriately initialize, verify and validate the models (data challenge).

There is a vast amount of literature that has studied behavioral dynamics and the potential of behavior interventions in the context of environmentally friendly behavior (Wilson and Dowlatabadi 2007). This literature consists of a wide range of disciplinary perspectives, including social and environmental psychology, sociological theories, transition theory, marketing, micro economics, and behavioral economics (Steg and Vlek 2009)(Stephenson et al. 2010). While these studies provide valuable insights and add to the empirical foundation of these effects, the *data challenge* for a modeler assessing long term global trends is also, how to summarize and quantify these empirical findings consistently, keeping an integrated and long term perspective. Specifically, within the context of agent based modelling, a key question is whether we can actually identify these agents from the data, and are there persistent (also across regions) drivers of their behavior?

Analysis

The data used in this study was collected via two large-scale surveys: PENNY, conducted in Italy, Switzerland and the Netherlands, and COBHAM, conducted in Italy. 6,138 responses were recorded, containing information on socio-demographic and socio-psychological characteristics, dwelling and household characteristics, technologies and energy services used, and their metered final *electricity*

consumption[2]. By using large cross country data set the aim is to better understand persistent heterogeneous patterns and behavioural drivers of energy choices.
The data was processed to produce a set of main variables, which were then used to cluster the survey responses into groups and analyse between- and within-group differences. A set of secondary variables was also produced, which were not used for clustering but were analysed alongside the main variables. Table 1 provides an overview of all main and secondary variables (note that the last 3 variables were only present in the COBHAM dataset and are not analysed in the main cluster analysis).

The energy efficiency gap, lighting demand and energy service index used in the cluster analysis are indicators that have been constructed, based on the information collected in the survey and the electricity consumption data, which is explained in more detail below. The cluster analysis was performed on these three variables combined with the electricity consumption. The clusters were then use to characterise the agents in the MUSE model.

[2] There were a large number of missing responses for metered electricity consumption in the Netherlands, leading to an under-representation of data from this country.

Table 1: .Main variables used for the cluster analysis and secondary variables to analyse cluster characteristics.

Main variables	Categories						
income class[3]	0-1000	1000-2500	2500-3500	3500-5000	5000-7000	>7000	
age range[4]	<15	15-24	25-44	45-64	65+		
education level	primary or lower	lower secondary	vocational/ upper secondary	university (3-yr)	university (5-yr/ postgrad)		
household size	1-person	2-3 people	4-5 people	6 or more people			
environmental preference aggregate[5]	very low	low	slightly negative	average	slightly positive	high	very high
absolute efficiency gap (quintile)	very low	low	medium	High	very high		
relative efficiency gap (quintile)	very low	low	medium	High	very high		
sign of efficiency gap	negative (efficient)	positive (inefficient)					
lighting demand (quintile)	very low	low	medium	High	very high		
weighted appliance demand (quintile)	very low	low	medium	High	very high		
annual electricity consumption in 2016 (quintile)	very low	low	medium	High	very high		

[3] Income was standardized between the two datasets using publicly available tax band information and combining the income classes into sextiles.

[4] Age was standardized into ranges under UNStat guidelines.

[5] The environmental preference aggregate variable was produced by averaging each respondents' self-reported importance of environmental value, morality, identity and social approval. The averages were standardized and split into 7 quantiles.

energy-saving investments in 2016[6]	nothing	\$0-50	\$50-100	\$100-500	>\$500		
risk preference (quintiles)	very risk-averse	risk-averse	neutral	risk-prone	very risk-prone		
Secondary variables	**Categories**						
behaviour – switching off lights	never	Rarely	sometimes	regularly	Always		
behaviour – unplugging appliances	never	rarely	sometimes	regularly	Always		
dwelling size (quintile)	<50 m^2	50-100 m^2	100-200 m^2	200-300 m^2	300-400 m^2	>400 m^2	
energy literacy[7]	low	medium	High				
home ownership	yes (owner-occupier)	no (tenant)					
share of LED lighting	less than 50%	more than 50%					
owns "luxury" electrical item?[8]	yes	no					
altruism	Continuous						
hedonism	Continuous						
importance of wealth	Continuous						
length of tenure	Continuous						
environmental value	Continuous						
environmental morality	Continuous						

[6] This variable was only recorded in the COBHAM survey.

[7] Low, medium and high energy literacy are equivalent to correctly answering none, one and two, respectively, of the following question

[8] Ownership of a "luxury" electrical item is defined as owning one of the following: home theatre system, sauna, solarium, swimming pool, water-bed, Jacuzzi, aquarium or terrarium.

environmental identity	Continuous
environmental social approval	Continuous
bulbs per m^2	Continuous
risk preference[9]	Continuous

2.1.1 Methods

Energy service indicators

In demand-side mitigation scenarios a distinction can be made between *service demand reduction* and *energy efficiency* improvements to reduce energy demand (Fell 2017). Changes in energy service could be seen as lifestyle change, while changes in energy efficiency related to technology choices (Creutzig et al. 2018). To distinguish between these two factors contributing to energy consumption an energy service index is computed.

The data analysis focuses on the appliances and lighting energy services, since electricity consumption is collected. Those households that had electric heating were taken out of the data sample (in the PENNY survey this was <5%). The expected electricity consumption from lighting electricity is calculated, based on survey responses on floorspace, the number of lightbulbs, and the share of efficient lighting. This is subtracted from the metered electricity data to estimate the appliance electricity demand.

Key drivers of expected appliance electricity demand, that relate to service, are number of appliances and appliance type (Cabeza et al. 2014). Both in the PENNY and Cobham survey there are questions asked that relate to number of appliances,

[9] This variable was only recorded in the COBHAM survey, as the self-reported risk tendency of respondents (0 being risk-averse and 10 being risk-prone).

type of appliance and appliance age, and efficient use. In PENNY there are also questions on the frequency of appliance use. The type of appliance and the efficient use questions differ per survey. Our approach is first to analyse for each survey the significance of each component regression analysis in relation to the electricity consumption.

Based on the results, for each household a weighted sum of lighting, fridge, dishwasher, dryer, washingmachine, tv and luxury appliances is calculated, used as appliance and lighting service level indicator. The weights given to the appliance type are based on a regression analysis performed against the metered data, where the weights agree approximately with the annual electricity consumption of the specific appliance. In this way, the energy service index is an approximated electricity consumption for the level of service. This value is compared to the actual energy consumption.

For each household there are three efficiency indicators based on the computed energy service index:

- The absolute efficiency gap: the difference between the actual electricity consumption and the energy service index, which could be a postive or a negative value.
- The relative efficiency gap: the proportion of the absolute efficiency gap compared to the electricity consumption, as an indicator of the size of the gap.
- The sign of the efficiency gap (negative or positive, referred to as “dwelling efficiency” in this paper): the difference between the metered and estimated electricity consumption, indicating whether a household is efficient (negative efficiency gap) or inefficient (positive efficiency gap).

Clustering method

The clustering was conducted on the continuous demand-related variables (lighting demand, appliance demand and absolute efficiency gap). By clustering the demand variables households are grouped that have similar type of energy demand. Then the socio-demographic and environmental preference variables of these clusters are analyzed to understand household characteristics and behavior drivers.

Ward's linkage clustering was conducted to identify the optimal cluster solution, and k-means clustering, (squared Euclidean distance similarity measure) for detecting the optimal cluster solution and producing the actual clusters for further analysis. The optimal cluster solution was chosen using a combination of the Calinski-Harabasz and Duda-Hart stopping rules and an analysis of variance (ANOVA) to examine within-cluster variation of the clustering variables for different cluster solutions.

An additional clustering was run on the dummy variables of the socio-demographic and environmental preference variables (Ward's linkage clustering and k-means clustering, Jaccard dissimilarity measure).

Cluster analysis

The cluster analysis consisted of a series of tests of differences (Kruskal-Wallis, ANOVA and (post-hoc) Dunn and Tukey tests) in all main and secondary variables between clusters, the comparison of means (continuous variables) and the distribution of categories (ordinal variables) between clusters, and fitting regression models to describe the relationship between variables. Regression models were fitted to the whole population as well as to each cluster. The continuous variables were modelled using heteroskedastic linear regression and the ordinal variables using ordered probit and logit models or, where the assumptions of multi-collinearity and proportional odds were violated, a generalized logit model.

All analysis was conducted in STATA v.12.

Residential Buildings Simulation Module

The above analysis is used to improve, calibrate and test the Residential Buildings Simulation Module (RSBM), which is part of the new whole system integrated assessment model called MUSE (Sachs et al. 2019). RSBM is an ABM for representing individual energy efficiency investment decision-making in the residential sector. The model framework is based on the Theory of Planned Behaviour (Ajzen 2001) and is constructed as a step-wise decision-making process for selecting and implementing energy-saving technologies and behaviours. In the model people's attitude towards technologies and technological changes are accounted for as well as the effects of policy. The RBSM applies a bottom-up approach to the technology characterization, based on unit technology cost, efficiencies, lifetime as well as emissions for 70 different technologies. While RBSM is a global simulation model, disaggregated into 28 regions, this first analysis focuses on the European regions. The heterogeneity in the agent behaviours is captured by segmenting the population into agent groups, based on the above described cluster analysis. These groups are then linked to certain energy service levels, based on their household and dwelling characteristics, and with different rules for searching for and deciding to invest in a technology based on the previously identified relationships between agent characteristics and agent behaviour rules. The combination of agents' energy service level, choice of household technologies and energy consumption behaviour determines the final household energy consumption.

2.1.2 Main results

Cluster results

The k-means clustering based on demand variables produced an optimal solution of 10 clusters containing 4,874 responses. 5 of these clusters were too small to include in further analysis[10], mostly due to the relative paucity of electricity consumption data. The remaining clusters (clusters 1, 3, 5, 7 and 8) are described below.

The cluster sizes varied significantly, and 4 out of the 5 clusters had an over-representation of responses from one country (Table 2), which should be considered in the further analysis of the clusters. Most variables showed significant differences between clusters (Table 3[11]); no significant differences were found

[10] Detail the criteria for considering them too small.

[11] The p-values are reported for the Kruskal-Wallis tests that accounted for ties in the data.

between clusters for household size (although significant at p<0.1), environmental preference aggregate, environmental value, morality or approval, altruism or hedonism. This was confirmed by post-hoc tests of difference.

The main characteristics of agents grouped in each cluster are highlighted below in Table 4.

Table 2: Size of clusters and over-representation of data from countries

Cluster	**Number of responses**				**Over-representation**
	Italy	**Switzerland**	**Netherlands**	**Total**	
1	643	125	39	807	
3	150	147	21	318	Swiss and Dutch
5	319	86	40	445	Swiss and Dutch
7	1204	70	34	1308	Italian
8	1538	116	36	1690	Italian

Table 3: Significance of differences between the 5 clusters

Variable	**Significant differences between clusters?**	**Variable**	**Significant differences between clusters?**
Income class	Y	Home ownership	Y
Age range	Y	Environmental value	n (p=0.55)
Education level	Y	Environmental morality	n (p=0.87)
Household size	n (p=0.051)	Environmental identity	Y
Environmental preference aggregate	n (p=0.46)	Environmental approval	n (p=0.55)
Energy literacy	Y	More than 50% LED share	Y
Electricity consumption	Y	Altruism	n (p=0.18)
Lighting demand	Y	Hedonism	n (p=0.21)
Appliance demand (weighted)	Y	Wealth value	Y
Efficiency gap	Y	Dwelling size	Y

Behaviour: switching lights off	Y	Ownership of luxury electrical item	Y
Behaviour: unplugging appliances	Y	Length of tenure	Y

Table 4: Key characteristics of the 5 clusters

Cluster	**agent attributes**						
	education[12]	**age**[12]	**household size**[12]	**income**[12]	**environmental preferences**[12]	**energy literacy**[12]	**behaviour: switching lights off**[12]
1	Vocational/Upper Secondary	45-64	2-3 people	mix	medium	medium	Always
3	Vocational/Upper Secondary	45-64	2-3 people	high	medium	medium	regularly/always
5	Vocational/Upper Secondary	45-64	2-3 people	mix	medium-high	medium	Always
7	Vocational/Upper Secondary	45-64	2-3 people	mix	medium	medium	Always
8	Vocational/Upper Secondary	45-64	2-3 people	low	medium	medium	Always
Cluster	**agent attributes**						
	behaviour: unplugging appliances	**lighting demand**[13]	**weighted appliance demand**[13]	**electricity consumption**[13]	**absolute efficiency gap**[14]	**relative efficiency gap**[12]	**efficiency of dwellings**[14]
1	mix	medium	high	low	low	high	Efficient
3	mix	high	high	high	medium-low	low	Mix
5	mix	medium	medium	high	high	medium-high	Inefficient
7	mix	low	low	medium-high	high	low	Inefficient
8	mix	low	low	low-medium	medium-low	mix	Efficient

Cluster descriptions

The clustering is driven primarily by the dwelling efficiency and the size of the absolute and relative efficiency gaps.

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12 Reported values take up a more than 40% share.

13 Based on mean values

14 Reported values take up more than 80% share.

Cluster 1 is *comfortably efficient*, living in exclusively efficient dwellings with large relative efficiency gaps despite a tendency for higher appliance demand. Members of this group are relatively young, tend to live in slightly smaller households and have the lowest residence times of all groups. They are the best at unplugging their appliances, despite being slightly less concerned about the environment than other groups.

Cluster 3 is a *well-off, potentially efficient* group, with 76% of members living in efficient dwellings, but with small relative efficiency gaps and the highest lighting and appliance demand of all groups. Members have higher education and income levels and are slightly older, more energy literate and less likely to switch lights off than other groups. They have slightly larger household sizes, and thus live in slightly larger dwellings, and value wealth a highly.

Cluster 5 is an *inefficient high consumer* group, whose members live exclusively in inefficient households, have medium-high relative efficiency gaps, and consume the most electricity of all groups. They are fairly well-educated and have high environmental preferences, but are the worst at unplugging appliances of all groups.

Cluster 7 is an *inefficient low consumer* group, with the lowest overall appliance demand and second-lowest lighting demand, living almost exclusively in inefficient households with small relative efficiency gaps and medium levels of electricity consumption. They have the smallest households of all groups, are relatively low-educated and live in smaller dwellings and have longer residency times than most other groups.

Cluster 8 is also a low consumer, but lives almost exclusively in efficient housing (92% of group) with small-medium relative efficiency gaps. Members of this group are have the lowest income levels, are slightly less energy literate and live the smallest dwellings of all groups, despite having a similar household size distribution to the comfortable efficient group. This group is *resource-constrained, but potentially efficient*.

As the clusters were strongly differentiated by dwelling efficiency and the relative efficiency gap, a regression analysis was conducted to evaluate the hypotheses that these two variables are affected by socio-demographic indicators, energy efficient behaviour and environmental preferences[15]. It should be noted that although the models could not validate any hypotheses (due to the non-normal distribution of regression residuals), the coefficients of the predictor variables are unbiased and can be used to trace the contribution of indicators[16].

Regression models fitted to dwelling efficiency showed that higher income, larger households and older age increased the likelihood of living in an inefficient dwelling, at population level. At cluster level, the well-off potentially efficient group was driven only by income ($p=0.015$) and the resource-constrained potentially efficient

[15] In reality, they are likely to also be driven by "technical efficiency" characteristics of the dwelling, such as insulation levels; however, the only technical efficiency component recorded in this study was the proportion of LED light bulbs (higher or lower than 50%), which had little impact on the efficiency of the dwelling and the size of the relative efficiency gap. Therefore, the results presented in this section focus on analysing how socio-demographic indicators, rather than technical efficiency characteristics, drive dwelling efficiency and the relative efficiency gap.

[16] In ordered logit and probit regressions, increasing the predictor variable by 1 unit (i.e. moving between different consecutive levels) results in an increase of *coefficient* in the log or probit odds likelihood of being in a higher efficiency gap category. A negative coefficient will mean a decrease in the likelihood of being in a higher efficiency gap category. Therefore if increasing income from level 3 to level 4 results in a coefficient of -1.47 with $p<0.05$, this means that by moving from level 3 to level 4 of income, there will be a 1.47x decrease in the likelihood of being in a higher efficiency gap category. The sign of the coefficient determines the effect of increasing the predictor on the response variable (in this case, increasing the predictor decreases the response variable) and the size of it relative to the other significant coefficients determines the size of the change in response variable when increasing the predictor (e.g. if the coefficients get smaller, it means that the effect of increasing the predictor on the response variable gets smaller).

by household size ($p=0.009$) and by income at $p<0.1$ ($p=0.056$)[17]. Like the population-level regression, higher income and larger households predicted a higher likelihood of living in inefficient dwellings.

The contribution of socio-demographic indicators to the relative efficiency gap was more varied. At population level, only household size had a significant effect: larger households had an increased likelihood of having smaller relative efficiency gaps, apart from the largest household group ($p<0.05$). At cluster level, income also played a significant role: in the inefficient high consumers group, wealthier households are less inefficient ($p<0.05$), as are wealthier households in the inefficient low consumers group, but only above the threshold of €3500/month, and this effect decreases with increasing income. In the resource-constrained group, both higher-income and larger households (apart from the largest household size) have lower relative efficiency gaps, and thus a higher likelihood of either being very inefficient or very efficient[18]. In the remaining two clusters, neither income nor household size contributed significantly ($p<0.05$) to determining the size of the relative efficiency gap.

[17] Note that the other 3 clusters could not be fitted with regression models due to having only one level of the dependent variable (exclusively efficient or exclusively inefficient dwellings).

[18] All results are derived from ordered probit regression models.

Figure 1: Key characteristics of 5 clusters.

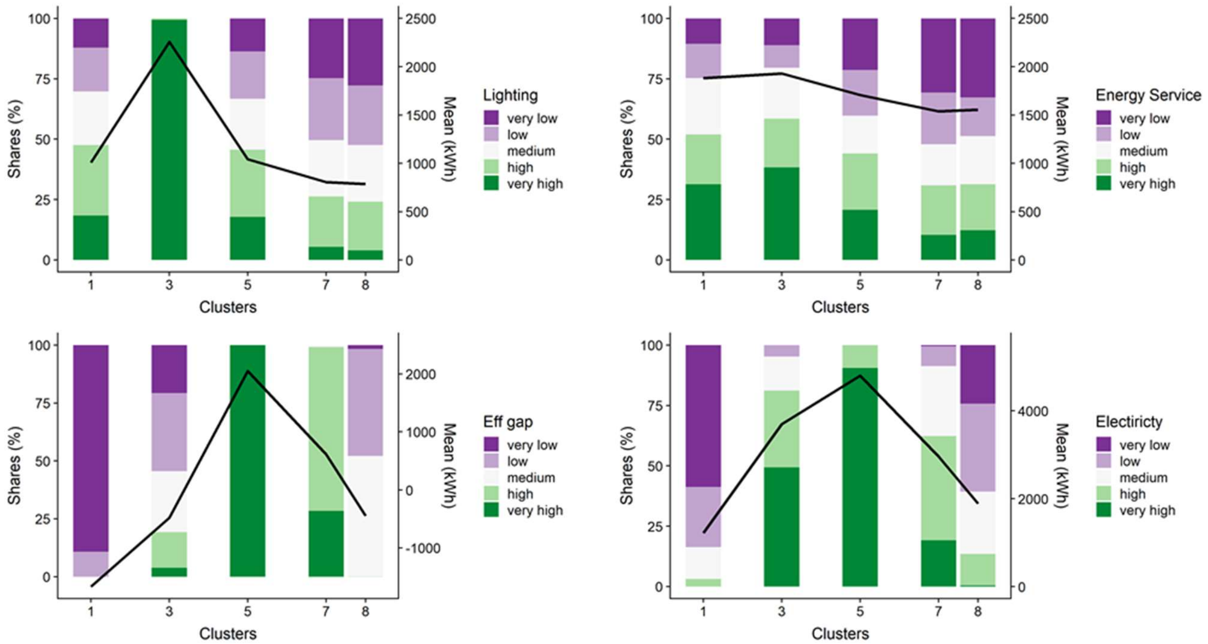


Figure 2: Socio-demographic indicators in the 5 clusters

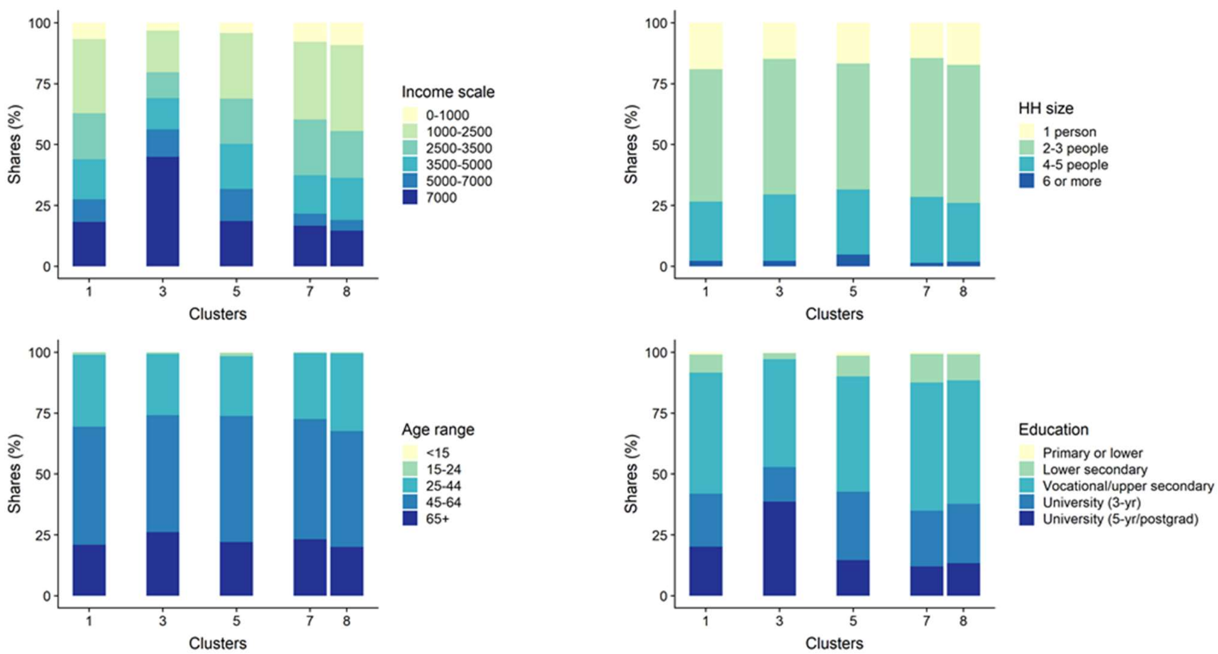


Figure 3: The environmental preference, energy literacy and energy efficient behaviour of the 5 clusters

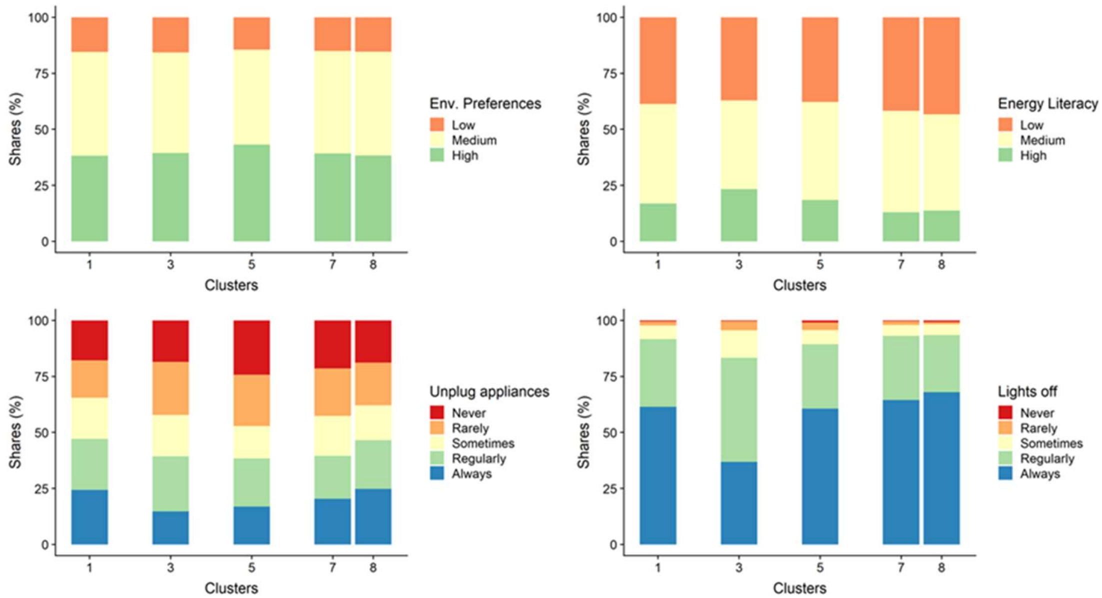
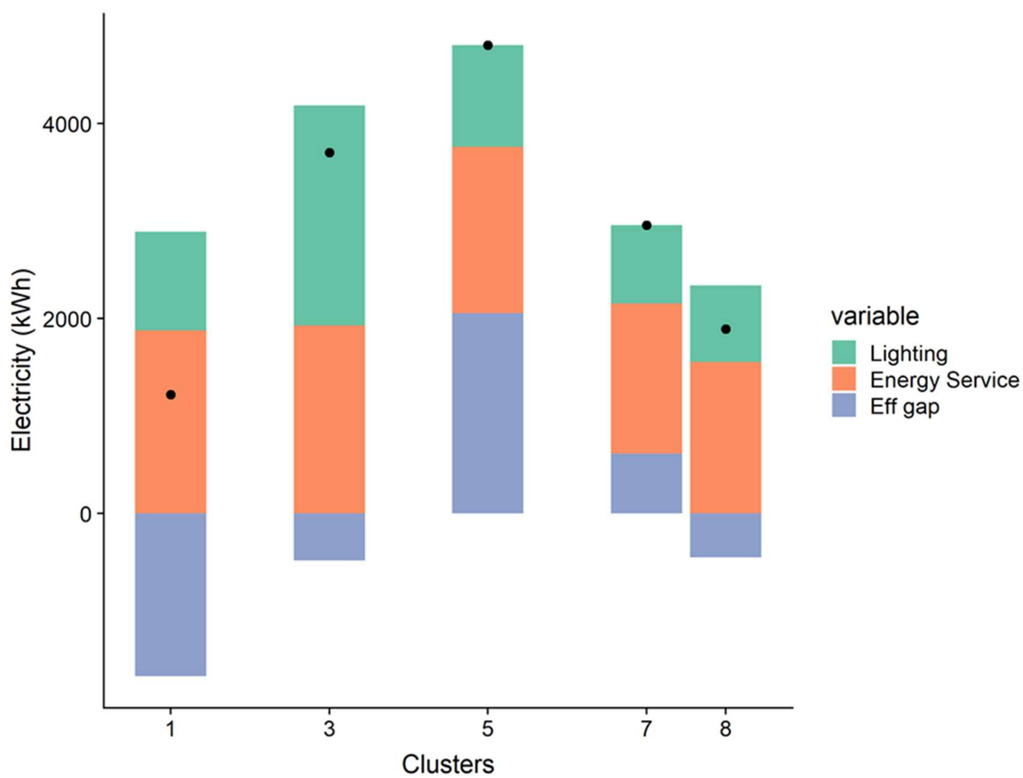


Figure 4: Annual electricity consumption in each cluster (indicated by the dot), which is the sum of the components (lighting and weighted appliance demand, and absolute efficiency gap)



Summary and key points

The cluster analysis demonstrates that groups of respondents with similar consumption and demand profiles exhibit a large variation in socio-demographic indicators, energy efficient behaviour and energy-saving investments. Therefore, it is not straightforward to identify based on socio-demographic indicators or preferences households' energy consumption behaviour. The clustering has shown that in terms of energy demand variables there is large distinction and thus heterogeneity between households, but the data does not allow us to recognise who these distinct groups acting in a certain manner are.

However, several key patterns have been identified, which can be applied to a modelling framework based on representative agent groups. Firstly, at population level, higher income drives higher demand, but not higher consumption: the highest-demanding groups are not the highest-consuming groups. However, within the sub-populations of overall efficient (groups 1, 3 and 8) or overall inefficient groups (groups 5 and 7), income drives both demand and consumption. Secondly, younger, lower-income respondents with smaller household sizes are more likely to live in efficient dwellings overall; however, there are group efficiency "thresholds" past which this trend reverses: between the resource-constrained potentially efficient and comfortably efficient groups, the older, wealthier group is the more efficient one. These observations show that, while income drives demand, its effect on consumption is modulated by the overall efficiency level of the dwellings (dwelling efficiency and the relative efficiency gap), which in turn is driven by income and household size, with income having the strongest effect.

2.1.3 Interpretation of the data for the MUSE model

To provide an empirically grounded model, the above results are used as a basis for classifying and assigning attributes to the agents in the MUSE ® RBSM agent-based model. The sub-set of clusters that contained data on energy efficiency investment levels (clusters 1, 5, 7 and 8) were used as a basis for defining groups of agents with different levels of improvement potential and drivers for investment. The scope of defining and modelling these agents was extended from the survey data to the building sector of the EU-18 region.

Because of the large variation in socio-demographic indicators, the age, income and household size distributions within each cluster were linked with data from the European Union Statistics on Income and Living Conditions (EU-SILC), to determine the overall share of the European population represented by each agent. To account for the within-cluster differences in service level, the range of electricity demand in each cluster is split into 5 further sub-ranges, with each sub-range being assigned to an agent "clone" with the same socio-demographic profile as the rest of the cluster. This allows the model to capture the demand heterogeneity within agent groups of similar service levels. A similar procedure is used to assign different efficiency levels to the initial technology stock of each agent.

The analysis of improvement potential and investment levels also produced insights that were used to define and make assumptions about the drivers of investment behavior for each group of agents. The investment of agents is mainly driven by the improvement potential of their dwelling, by their energy-saving behavior and by having sufficient income to make investments. These investment drivers are translated into objectives assigned to the agents in the model, based on parameters assumed to change over time. The main objectives used in the MUSE ® RBSM agent-based model are:

- Capital cost – agents will be tolerant of a certain capital cost based on their income constraints and risk preferences;
- Equivalized annual cost (EAC) – agents will seek to adjust their EAC based on income constraints and the dwelling improvement potential;
- Fuel consumption cost – agents will be tolerant of their fuel consumption cost based on the improvement potential of their dwelling;
- Efficiency – agents will seek to adjust the efficiency of their energy use for non-economic reasons
- Emissions – agents will seek to adjust their emissions levels based on their preferences such as environmental awareness.

An overview of how the identified categories of investment drivers are translated to the objectives of agents are given in Table 5.

Table 5: Translating the cluster findings in to objectives applied to the different agents in the model.

Cluster	Findings of cluster analysis	Link to objectives
Cluster 1 – AGENT 1	Not driven by improvement potential or income; Driven by good energy-saving behavior, high energy literacy, high risk appetite	Driven by emissions and efficiency as objective; Low maturity threshold enabling the acceptance of new technologies; Capital cost may still be a constraint in this low-income group
Cluster 5 – AGENT 2	Driven by improvement potential and income	Driven by efficiency and fuel consumption; Least capital constraint due to high income, thus driven by EAC
Cluster 7 - AGENT 3	Somewhat driven by improvement potential; Not constrained by income; Possibly constrained by low energy literacy	Somewhat driven by fuel consumption costs; Higher maturity threshold required, potentially causing investment in similar technologies or fuel types
Cluster 8 – AGENT 4	Driven by improvement potential Constrained by income Possibly constrained by low energy literacy	Driven by efficiency and fuel consumption costs Highly constrained by capital cost; Higher maturity threshold

2.1.4 Model application

The complexity of global IAMs, which cover the whole energy system, leads to a need for simplification of modules representing individual energy sectors. In its current version, the MUSE RBSM is designed to capture the most relevant aspects that drive consumer technology choice and investment on a regional scale. To account for all findings of this analysis, the MUSE ABM code is extended to reflect the variation of service demand levels within each cluster, as shown in the previous section. These are integrated as additional agent attributes and stochastics are added around the parameters of agents' decision heuristics (e.g. weights assigned to the agents' objectives when deciding whether or not to invest in a technology) to capture the heterogeneity in decision making, and thus in energy efficiency investment, within a cluster.

The application of these findings to the MUSE RBSM is designed to demonstrate the differences between an empirically-grounded model initialization, compared to one determined by macro-economic indicators. In the following section, we present the results of this comparison, highlight the benefits of the empirically-grounded model and comment on its suitability to model the residential building sector. Our results are formulated as a case study of the RBSM of the MUSE EU18 region, in which we analyze the technology diffusion for different agent parameterizations and model extensions. First, a comparison is carried out between a macro-economically-driven agent parametrization and the cluster-driven parameterization, without varying the service level within each cluster or adding stochastics. In the second step, different scenarios are simulated to examine the effect of adding within-cluster service level variation and stochastics on the outlook for the European energy system. We thus use three cluster-driven models with different agent parameterization in these comparisons:

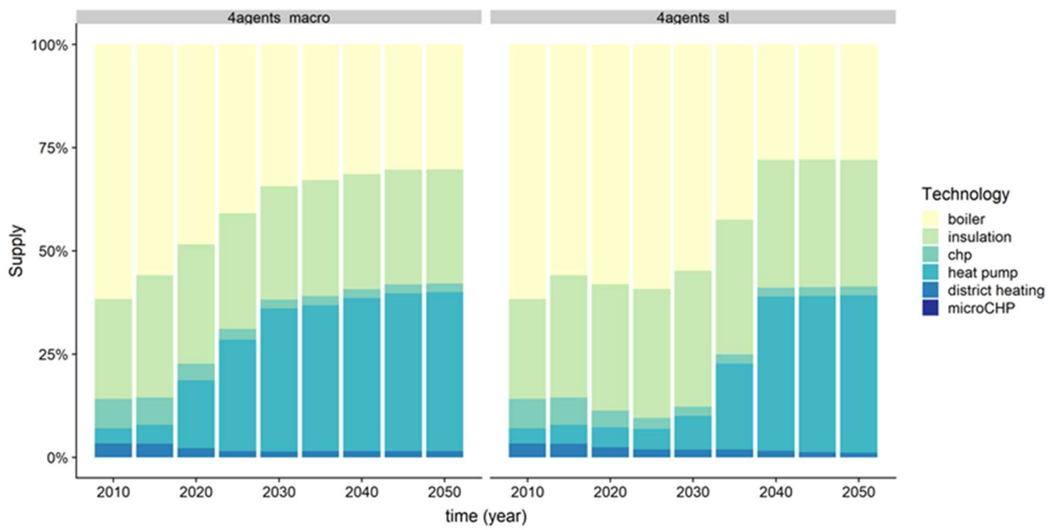
1. A model where the service level is varied within each cluster, but no stochastics are added;
2. A model where the service level is varied within each cluster and stochastics are added
3. A model with a constant service level across all clusters and added stochastics

Each model contained 80 agents, simulating 5 agent clones for the 5 sub-ranges of service level in each cluster (the clones were identical for the third model described above), in each of the 4 clusters. Each agent clone was duplicated to indicate whether their investment was in a new residential building or an existing one (retrofit). All scenarios are run with a carbon tax until 2050. The case study does not directly account for the changing carbon intensity of electricity, but rather considers the influence of the carbon price on the electricity price as a proxy.

2.1.5 Scenario results

Figure 5 presents the results for a macro-economic-driven in contrast to the cluster-based parametrization for the production of space heating technologies.

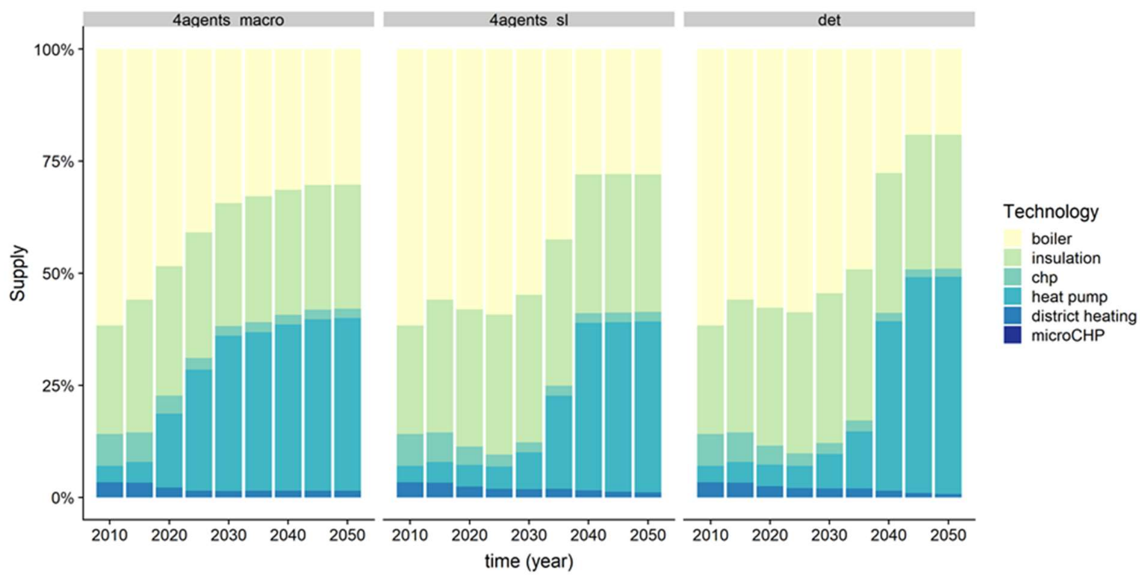
Figure 5: Technology penetration in the model formulation with left) macro-economic driven approach and right) cluster-based approach.



Comparison between the cases shows a broadly similar result in that heat pumps are adopted and replace conventional boilers leading to a similar technology landscape under both parametrizations in 2050. Looking at the transition phase from 2020-2040, results between the two models differ much more markedly. The macro-economic model adapts heat pumps directly, where the increase in heat pumps in the cluster based model occurs later but at a higher rate. The cluster-based model shows a distinct transition phase, with low-carbon boilers and insulation measures dominating the market until heat pumps eventually take over the highest market share. The different uptake patterns in particular are an effect of the difference in the percentage of the population represented by an agent with the same objectives, decision rules and search strategies. For example, assuming that all people with high income, high education and within a certain age range tend to adopt energy efficient technologies lead to an immediate update of heat pumps, and thus different diffusion patterns. Approaching the problem from the other side shows that a clustering based on energy demand and consumption results in agents with a large variation in socio-demographic indicators leading to different amounts of the population presented by one agent.

To capture the effect of adding within-cluster service level variation, five clones for all agents, each corresponding to a service level, are generated. Figure 6. shows that the integration of different service levels itself only has a minor influence on the overall update of the different technology groups resulting in a higher share of heat pumps by 2050. This difference is based on the correlation of energy demand level and household income, leading to a larger share of agents which presents people within this category that drive the investment in heat pumps. This result is nuanced by the fact that the ABM including clones selects a more diverse range of heating systems (e.g. different types of boilers), reflecting the diversity of agents.

Figure 6: Technology penetration in the model formulation with 1) macro-economic driven approach, 2) cluster-based approach and 3) cluster-based approach including different service levels (from left to right).



2.2 Improved building stock and insulation investments in EDGE

Globally, 30% of the building sector energy demand comes from heating and cooling, with this percentage raising to 50% in cold climate countries. It is recognized that in order to achieve energy demand reductions for the highlighted end-uses, improving the envelope insulation levels must be a very important step, since it also allows for downsizing of the heating and cooling equipment (OECD 2013). The thermal conductivity of building envelope components (namely "U-value") is the representative parameter for thermal performance of buildings which plays an important role in the determination of buildings energy consumption. In this second part of the deliverable analyse long term building stock dynamics in a global model to better understand the how building inertia interacts with building policies and the European level as well as the global level.

2.2.1 Methods

The IAM buildings' model used for this work is the Energy Demand GEnerator (EDGE), developed by the Potsdam Institute for Climate Impact Research (PIK) (Levesque et al. 2018). It can be defined as a bottom-up, statistically-based simulation model, which is multi-regional and employs a long-term point of view. While it can be used as a standalone buildings module it can also be coupled to larger IAM modelling frameworks. For this research the model has been modified and significantly extended in order to include key insulation measures, as well as building vintages. These enhancements allow the model to assess the implications of energy and bulding policies on global energy demand. In order to do so, historical data on residential building thermal performance, gathered by the EU commission database (EC 2019b) were analyzed, to understand the main determinants of the insulation levels over regions and time, represented by the thermal conductance of building envelope components: namely, U-value. By means of a regression analysis, the influence of several variables was tested. Moreover, an extensive literature review was performed, aiming at understanding the main drivers of renovation investments and possible policy measures to spur the improvement of energy efficiency in buildings. In addition, indications on state-of-the-art and future perspectives insulation technologies were researched.

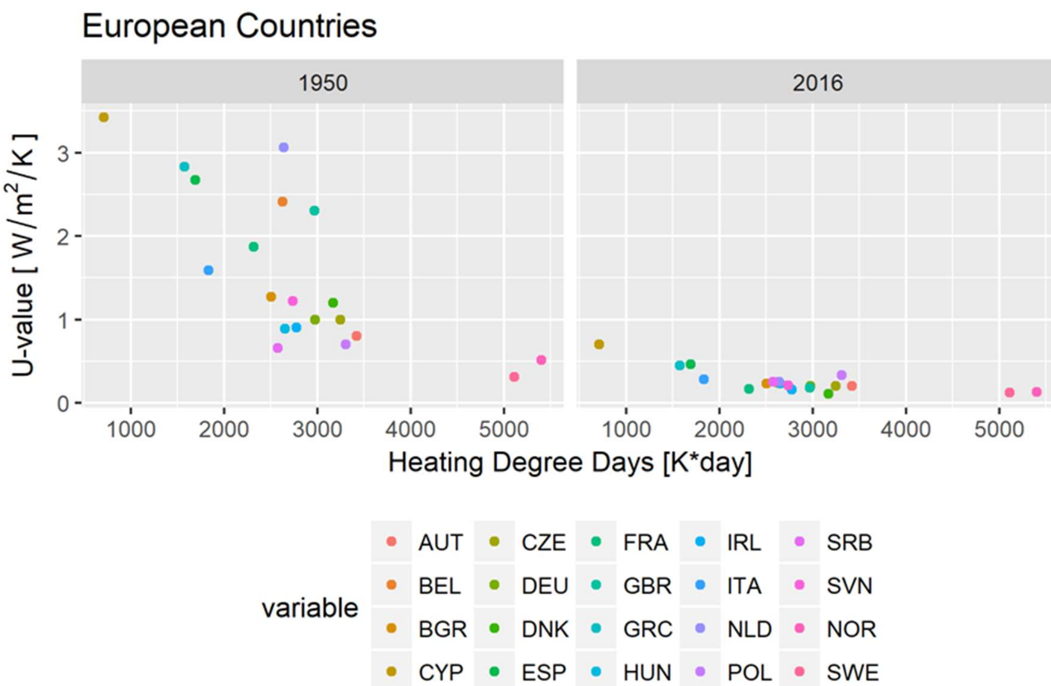
Based on the collected information, the current EDGE U-values module was reviewed and updated. First diagnostics of the results were carried out, in order to understand the sensitivity that the new module calculations showed with respect to input parameters. Then, the model was extended to the global level and a lack of data was encountered, compared to the wide amount of detail collected for Europe. Therefore, by means of both region-specific indications from the literature and assumptions based on European trends, input data were computed for all the world regions.

To validate the new developed module projected values were compared to past European trends of insulation levels. The EPBD was simulated both at the European and at the global level, in order to respectively quantify existing gaps with the current trends and to evaluate how the total energy demand would develop if this policy is applied to each world region. Finally, the robustness of the results is checked by means of an extensive sensitivity analysis, in order to account for uncertainties in input parameters.

2.2.2 Main results

The data analysis shows that for the oldest vintages, U-values are spread over a wide range, mostly depending on the climate. However, especially for vintages build after the 1980s, a steep increase in the insulation levels can be observed, with a convergence to very low U-values for the newest vintages. This shows the large impact of the implemented energy policies carried out all over Europe. U-values are found to be strongly related with climate, measured in Heating Degree Days (HDD) and Cooling Degree Days (CDD), and time. Energy prices and income are important drivers, affecting investment decision and the implementation of buildings policies. No significant differences on buildings U-values between the residential and services sub-sectors were found.

Figure 7: U-Value for different climates, across countries, build in 1950 compared to 2016

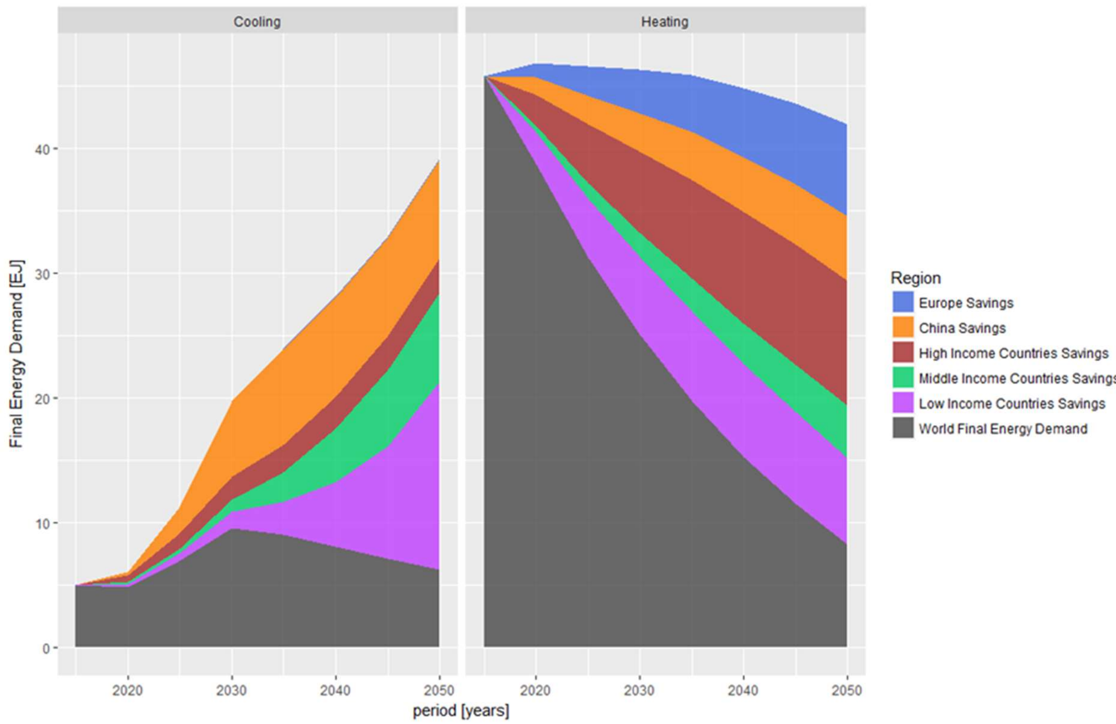


The investment payback time (PBT) represents one of the major barriers for renovation, over several European regions (Heiskanen et al. 2012). New buildings however generally follow the cost-optimality principle, outlined in (Hermelink et al. 2013). Therefore, the estimation of future buildings thermal performance was based on the optimization of the Net Present Cost (NPC). Investment costs of the available and new insulation technologies are estimated, while savings are calculated based on the insulation thermal conductivity, energy prices, energy carries shares and end-uses efficiencies and finally on the discount rate. Renovation and new construction are modelled separately as they follow different decision rules, taking into account for both of them the opaque and glazed surfaces

Building stock and U-value modules coupling

Figure 8 presents the main results of the model, calibrated to current trends. At the global level, more than half of the heating energy demand currently comes from the richest countries and the regional shares do not substantially change until 2050. Renovation of the current building stock and increasing end-use efficiency will make overall final energy demand decline. Conversely, the expected income growth in low income countries and China is estimated to trigger cooling demand growth, with an 8-fold increase from 2015 to 2050. Final energy demand is eventually estimated to increases by 60%, compared to 2015 levels.

Figure 8: Heating and Cooling Final Energy Demand estimations, divided by groups of regions

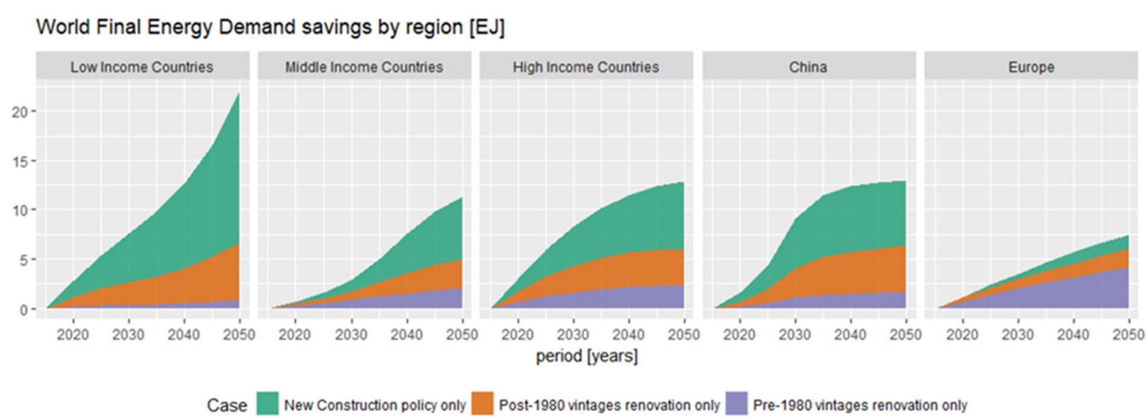


European Policy for Buildings Directive objectives

The model projects that in Europe, final energy demand is expected to decrease by 20% by 2050, if the current trends are followed. The implementation of the European Policy for Buildings Directive is expected to drop the 2015 levels of final energy demand by 80% in 2050. Four fifths of this 60% additional decrease comes from the renovation of old buildings. The implementation of this policy in Europe would make the 2050 total final energy demand further decrease by 10%.. Implementing the same policy across the world would make the overall final heating demand decrease by 37 EJ with respect to the 2015 levels, while cooling demand would actually reach a peak and then decline, keeping in 2050 similar levels of 2015. A full implementeation of the two policies combined would results in 2050 final energy demand to be approximately equal to 15 EJ: an overall decrease of 80% compared to the expected 2050 level.

Increasing wealth and population levels in low income nations and China will similarly foster high levels of new construction as well, thus immediately implementing building codes can lead to significant energy demand reductions in the short and long term, given the long lifespan of buildings. Accordingly, China on its own would additionally save 6.5 EJ only by constructing nearly-Zero Energy Buildings from 2015 on, as Figure 9 shows. A key difference from Europe is that most of the regions show that at least 50% of the 2050 final energy demand savings would be due to the implementation of a nearly-Zero Energy Buildings new construction stock, with this percentage raising to 80% in regions such as India and Africa. This means that while in Europe renovation policies attribute to the largest share of energy savings, most of the other world countries would benefit mostly by new construction policies.

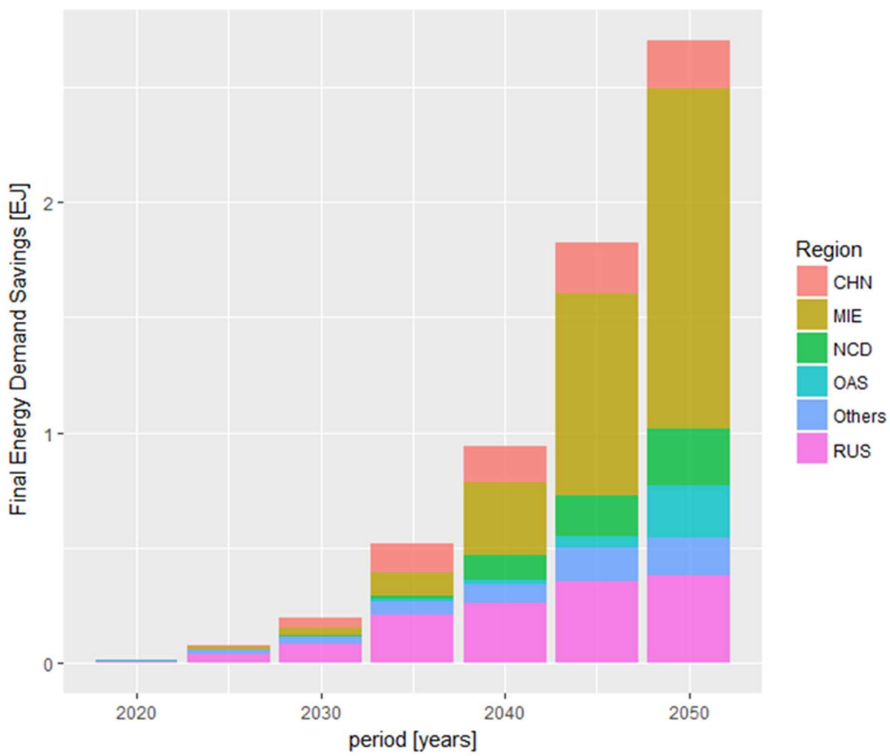
Figure 9: World final energy savings, divided by impact on the building stock



Energy price increase

Energy prices data were taken from a recent study in Nature Energy (Jewell et al. 2018), which also indicate the amount of fuel subsidies across different world regions. When implementing estimated energy price increases (+2%/y of electricity price, +2.8%/y for other carriers price until 2030 (EC 2019a)) into the model, it results that additional 1.5 EJ would be saved from the 2050 final energy demand in Europe. If a stronger price increase of 4.3%/y (Enseling and Loga 2012) is implemented, the gap among the EPBD objectives and the expected trends decreases from 7.5 to 5 EJ, thus it is reduced by one third. Subsidies on energy prices do not basically matter in the European region: only 0.5% of the 2050 final energy demand would be saved if they are removed. This percentage instead raises much more at the global level, where around 3% of the 2050 final energy demand would be saved, with Middle East providing 55% of the additional energy savings, as can be seen from Figure 10.

Figure 10: Final energy savings compared to the baseline, at the world level in case of subsidies reduction



Impact of parameter uncertainty

Country-specific implicit discount rates have been introduced to calibrate the model to current values, which also reflects the uncertainty related to starting values of input parameters. However, the development over time of such parameters is certainly not known, even if several assumptions can be found in the literature. Therefore, different tests were performed, making the most important parameters vary between reasonable ranges and accounting for the variation in results. For reasonable ranges of technology cost decrease, every additional 1%/y reduction in cost is estimated to reduce the total final energy demand by 4 EJ in 2050. A progressive shift towards 100% market share of the best-performing technology is instead more important, eventually achieving final energy eductions of 7.9 EJ.

For the poorest regions of the world a 15% implicit discount rate was computed. Assuming different rates of decrease of this parameter only slightly affects the results, since for instance the African income level remains really low, thus not stimulating increasing energy demand. Overall, the global 2050 Final Energy Demand increases by 2.1 EJ if no discount rate decrease is implemented, while it decreases by 2 EJ when a quicker reduction is assumed to happen. Developed countries showed an average discount rate of 5% from the calibration process. Increasing this parameter to a 7% level causes a global Final Energy Demand increase by 2.9 EJ in 2050, while convergence to a 3% level would cause it to be reduced by 3.2 EJ.

Different levels of renovation rate might strongly impact heating energy demand, since Europe is the region which is affected the most by this assumption. Total Final Energy Demand in 2050 changes from +3.5 EJ if no renovation happens to -2.4 EJ if renovation rates are tripled. Assumptions on the main socioeconomic drivers generate different dynamics across regions, which finally lead to similar levels of Final Energy Demand in 2050. If income levels grow and environmental awareness is raised, then developed countries will strongly reduce their heating demand, due to a less intensive use of heating equipment and to stronger technological development. However, developing nations will strongly increase their cooling consumption, due to increased wealth levels. Finally only when combining the best cases reported in the literature with increasing energy prices and renovation rates, the model estimates that the EPBD target set is ambitious but also potentially achievable

3. Improving the representation of consumer behaviour in WIOD CGE Model

Methodological, we build on the CGE model presented in D4.1. In our CGE simulations we analyse the importance of information and knowledge on energy costs on energy efficiency and generate scenarios to analyse the impact of misperceived prices on energy consumption and CO2 emissions in Europe.

3.1 Simulation strategy

We consider several scenarios that simulate households' electricity price misperceptions in energy service consumption. An overview of the sets of scenarios is displayed in Table 6.

Table 6: CGE model misperception scenarios[19]

Scenario		Simulation Description
1	MP	Electricity price misperception between -50% and +50%
1.1	NMP	Negative electricity price misperception of -50%
1.2	PMP	Positive electricity price misperception of 50%
2	SE	Increase in the elasticity of substitution in consumption (σ^{sz}(GER) = 0.5; 1.0; 1.2)

We define a region's misperception of the regional electricity price to be the relative deviation of the median of the regional consumers' price perception from the actual average regional electricity price including taxes in the respective country.

The results of the large survey sample conducted in this project indicate that there is no consistent misperception in one direction across Europe. Table 7 presents the results for Switzerland, the Netherlands, Italy and Germany.

[19] We further consider short-run ($\sigma^{ela}_{(GER)}$ = 0:2) and long-run ($\sigma^{ela}_{(GER)}$ = 0:4) scenarios.

Table 7: Electricity price misperception

Country	Average[a] [EUR/kWh]	Median[a] [EUR/kWh]	Actual[b] [EUR/kWh]	Misperception [%]
Switzerland	0.22	0.16	0.18	−5.47%
Netherlands	0.35	0.19	0.16	+18.75%
Italy	0.35	0.20	0.21	−4.76%
Germany	0.26	0.25	0.30	−16.67%

[a]*Source: Own calculations based on the large survey sample.*

[b]*Source: Eurostat* (2018)*, ElCom* (2018)*.*

Due to the wide range of electricity price misperceptions across Europe, we look at misperceptions in both directions, i.e. in the range between -50% and +50% of the real market price in our main scenarios (MP). For the representative German household in 2018 this range would imply a price perception between about 15 Cent/kWh and 45 Cent/kWh. By simulating this price perception range in the CGE framework, we are able to identify the main channels that are affected by the electricity price misperception.

Scenario 1.1 (NMP) and Scenario 1.2 (PMP) are special cases of the MP scenario and represent the extreme misperception values we simulate. In the NMP scenario, we simulate a -50% electricity price misperception and in the PMP scenario, we simulate a positive electricity price misperception of +50%.

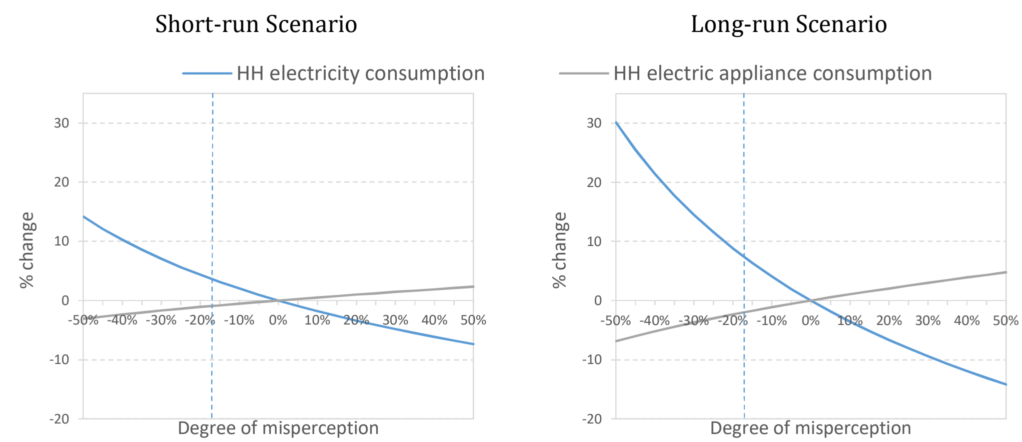
Furthermore, the short-run adjustments in the demand for household appliances responding to a higher or lower misperception in the electricity price can be assumed to be lower than in the long-run. There might simply be a degree of inertia in the consumption response, but it can also be assumed that expensive new appliances like washing machines or televisions are purchased with the longer-term view in mind, as these purchases are not every day decisions. We simulate this by accounting for a difference between short- and long-run elasticities between electricity and the electric appliance and assume a short-run substitution elasticity of 0.2 and a long-run substitution elasticity of 0.4 which is a quite conservative assumption (see e.g. Fischer et al. (2017), Lecca et al. (2014)). An increase in the elasticity translates into facilitating the household to switch to a more efficient technology and thereby reduce its electricity demand. A higher elasticity of substitution between electricity and appliance however, also implies that in the case of a negative misperception where the household undervalues the electricity price, the household will buy less new appliances and consume more electricity compared to a situation without misperception.

In the last simulation scenarios (SE), we briefly consider the case of an increase in households' willingness to shift their consumption from energy services to other consumption goods and vice versa. To accomplish that, we relax the underlying Leontief assumption between energy services and other, non- electricity, consumption goods in the household utility function and allow for substitution across energy services and other goods in consumption. This allows us to show what happens if consumer preferences change. The change in substitutability in this set of scenarios is combined with the previous scenarios to evaluate importance of this parameter on the model results.

3.2 CGE Results

We first simulate a wide range of possible electricity price misperceptions in Germany and compare the results with the benchmark situation without a misperception. A change in electricity consumption depends on the direction of the misperception and is linked to the use of more or less energy efficient appliances. Figure 11 shows the importance of the trade-of or adjustment process in energy service consumption that is represented by the households' ability to substitute electricity for more energy efficient appliances.

Figure 11: Relative change in energy service input consumption (MP Scenario)



The dashed blue line depicts the median misperception of -16.67% in Germany that was found in the large survey sample conducted in this project. Notice that we do not allow the substitution between energy services and any other consumption good at this point. Due to that, our energy service consumption does not change by much as consumption is not shifted to other goods. Therefore, the main decision that the household is making is how she is going to consume this service.

Compared to a situation in which households are fully informed a negative misperception of 50% of the (real) market price, leads to an increase in electricity consumption by 14.18% and a reduction of 3.08% in purchases of new electric appliances (see Figure 11, 'Short-run Scenario').

As demand for energy services change with respect to the equilibrium quantities, the prices need to change in order to restore the equilibrium between demand and supply. A misperception of energy prices hence has a significant impact on households' expenditure.

Figure 12: Relative changes in the expenditure on energy services

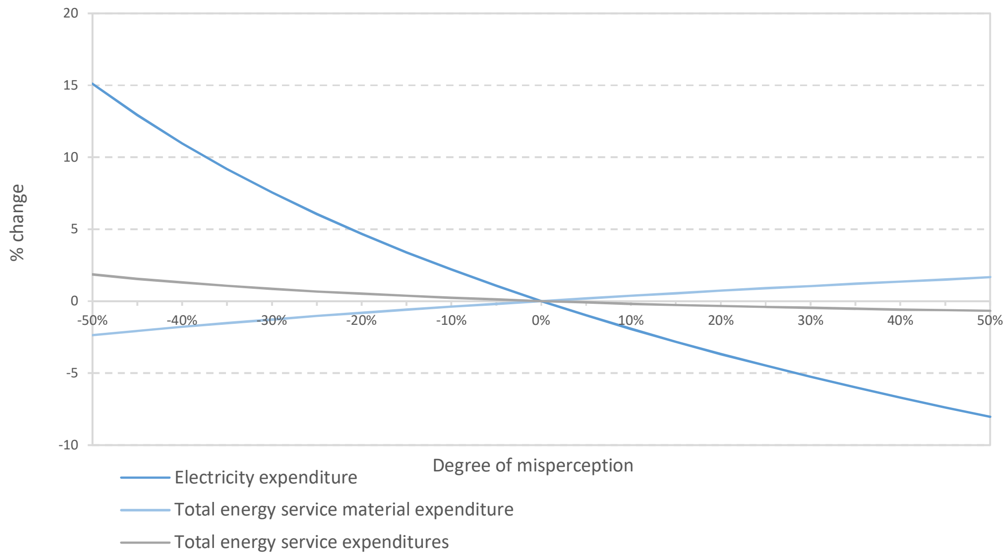


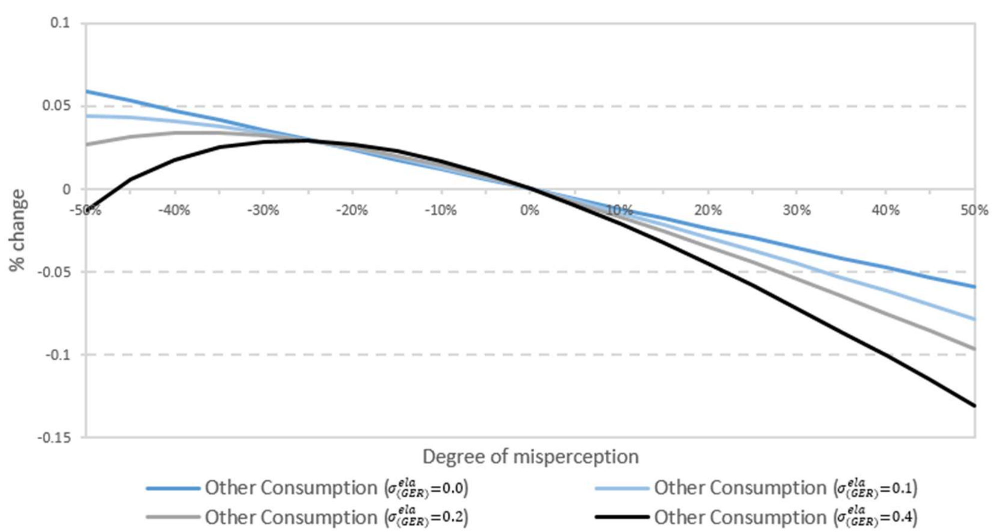
Figure 12 shows short-run changes of energy services expenditure, which is made of the expenditure on new appliances and electricity. A household that thinks the electricity price is 50% higher than the (real) market price will reduce its electricity consumption by 7.37% and increase its purchases of new electric appliances by 2.33%, increasing expenditure on appliances by 1.66%.[20]

A higher substitutability in the long-term more than doubles the effect of the price misperception in comparison to the short-term (see Figure 12, 'Long-run Scenario'). Misperceiving the electricity price to be 50% lower than it actually is leads to a 30.15% higher electricity consumption compared to the benchmark scenario with no misperception. It also results in a reduction of 6.88% in purchases of new electric appliances, diminishing expenditure on these appliances by 6.19%. If prices are misperceived to be 50% above their true level, households consume 14.17% less electricity and increase their electric appliance purchases by 4.77% and expenditure on the appliances by 4.13%.

[20] The elasticities of electricity demand are similar to those in Deryugina et al. (2017)and Alberini and Filippini (2011).

The misperception in electricity prices also has an impact on the consumption of other goods. As we do not allow for a substitution between other consumption goods and energy services at this point, possible changes in other consumption goods equals the relative change in energy service consumption, which is of course much lower in absolute terms. Figure 13 displays the impact of price misperceptions for various elasticities of substitution in the consumption of the energy service ($\sigma^{ela}{}_{(GER)}$ = {0; 0.1; 0.2; 0.4}). We observe that a negative electricity price misperception can lead to a decrease or an increase in the consumption of other goods depending on the ability or ease to substitute more electricity for appliances. We see a turning point in the increase in consumption of other goods for elasticities above 0.2 for a negative electricity price misperception above about 25%. The consumption change of other goods compared to the benchmark becomes negative for the long-term elasticity ($\sigma^{ela}{}_{(GER)}$ = 0.4) in case of a positive misperception but also in case of a negative misperception greater than 47%.

Figure 13: Relative changes in other consumption



The CGE model allows us to look at the impact of price misperceptions on the supply side of the market and how changes in electricity consumption of the households affect CO2 emissions in the economy. For the sake of clarity, we now consider two misperception scenarios. In the first scenario, we simulate a negative electricity price misperception of 50% (NMP scenario). In the second scenario, we simulate a positive misperception (PMP scenario), i.e. households think the electricity price is 50% higher than it actually is. Before we look at the different production sectors, we present some key macroeconomic indicators in Table 8.

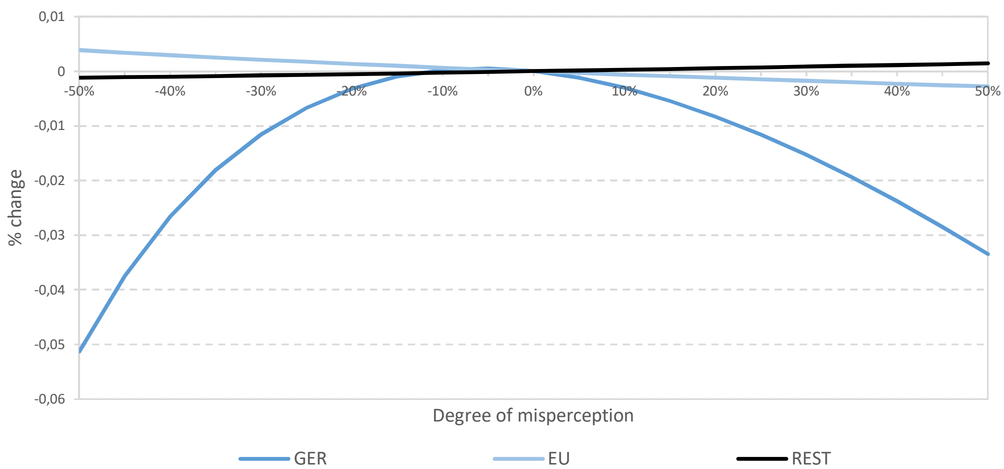
Table 8: Changes in key variables and macroeconomic indicators in Germany [%]

	NMP Scenario[b]		PMP Scenario[c]	
	SR[a]	LR[a]	SR[a]	LR[a]
GDP	-0.05	-0.15	-0.03	-0.03
Exports	-0.43	-0.77	0.33	0.54
Imports	-0.00	-0.02	0.01	0.03
CO_2 emissions	2.33	4.96	-1.19	-2.31

[a] SR: short-run; LR: long-run
[b] NMP: Negative electricity price misperception of 50%
[c] PMP: Positive electricity price misperception of 50%

Compared to a situation without an electricity price misperception, in the short-run NMP scenario, gross domestic product (GDP) in Germany decreases by 0.05%, household final consumption and CO2 emissions increase by 0.03% and 2.33% respectively. In the long-run GDP, household final consumption and CO2 emissions decrease by 0.15%, 0.01% and 2.31% respectively. Figure 14 shows the impact of misperceived electricity prices on GDP in Germany, Europe and the Rest of the world in the short-run.

Figure 14: Relative change in GDP compared to the benchmark

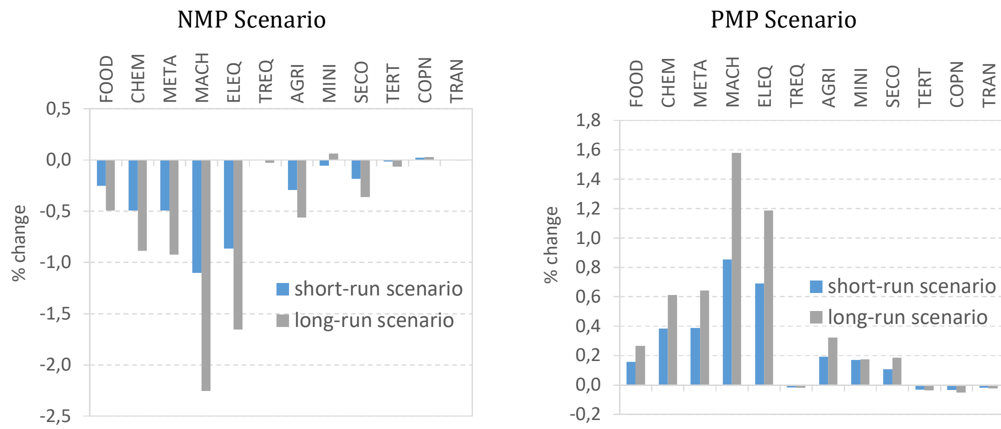


Just like in the case of a negative misperception, the change that is due to a misperception in a positive direction is rather small. Compared to a situation without any misperception, GDP and final consumption by households decrease by 0.03% and 0.10% respectively in the short-run scenario when households think the electricity price is 50% higher than it actually is (PMP scenario). In the long-run GDP decreases by 0.03% and household final consumption decreases by 0.13%. CO2 emissions decrease by 1.19% in the short-run and by 2.31% in the long-run PMP scenario.

The industry mostly affected by the behavioural shortcomings of the consumer is the electricity sector.[21] In the NMP scenario, electricity output increases by 4.58% in the short-run and by 9.75% in the long-run. In the PMP scenario, electricity production in Germany is reduced by 2.36% (4.55%) in the short-run (long-run) compared to a situation without electricity price misperception. As changes in the electricity demand lead to price changes, also other production sectors are affected. Figure 15 shows the relative changes in production of the other production sectors compared to a situation without a misperception for the two scenarios in the short- and long-run.

[21] As the changes are too large compared to the other sectors, the electricity sector is not shown in the figure for the sake of clarity.

Figure 15: Production change compared to benchmark



In the PMP scenario, the machinery sector (MACH) and electrical equipment (ELEQ) sector in Germany increase their output by 1.58% and 1.19% respectively in the long-run, compared to a situation without a price misperception. Furthermore, imports of electrical equipment increase by 0.97% in Germany.

The impact of a misperception of the electricity price in Germany on the European economy are rather small. European exports of electrical equipment used as intermediate and final goods decrease by 0.01% in the short-run and increase by 0.03% in the long-run in the NMP scenario, whereas total EU machinery exports decrease by about 0.03% in the short- and long-run. In the PMP scenario, European electrical equipment (machinery) exports increase by 0.03% (0.03%) in the short-run and by 0.02% (0.04%) in the long-run.

In the next step, we relax the Leontief assumption and present the results of a situation in which consumers are able and willing to shift away from energy services if the energy service composite good becomes more expensive. As the Leontief assumption prevents households from substituting energy services for other consumption goods, we see amplified effects in the energy service consumption if this substitution becomes easier. We conduct a sensitivity exercise with respect to the elasticity of substitution and depict the results for four different elasticities in the NMP and the PMP scenario in Table 9.

Table 9: Short-run changes in consumption and other key variables in Germany [%]

	NMP[a]				PMP[b]			
	$\sigma^{sz}_{(GER)}$							
	0.00	0.50	1.00	1.20	0.00	0.50	1.00	1.20
Energy services	0.03	1.11	2.13	2.52	-0.10	-1.04	-1.92	-2.25
Electricity	14.19	15.46	16.64	17.10	-7.38	-8.27	-9.10	-9.41
Electric appliances	-3.08	2.71	8.12	10.20	2.33	-2.76	-7.47	-9.25
Other consumption	0.03	-0.39	-0.78	-0.92	-0.10	0.26	0.60	0.73
CO_2 emissions	2.33	2.59	2.84	2.93	-1.19	-1.39	-1.58	-1.64

Short-run scenario: $\sigma^{ela}_{(GER)} = 0.2$
[a] NMP: Negative electricity price misperception of 50%
[b] PMP: Positive electricity price misperception of 50%

When we gradually increase the elasticity of substitution between energy services and other consumption goods in the utility function, households are increasing their energy service consumption. Compared to the main scenarios without substitution in consumption, in the NMP scenario, energy service consumption is increasing from 0.03% up to 2.52% in the short-run. In the PMP scenario, we observe that consumers are increasingly shifting away from energy service consumption by reducing their purchases of new appliances and electricity consumption.

Potential co-benefits that result from reduced energy demand like health benefits trough better air quality will have an additional effect on welfare. From a private perspective, households might invest too much in energy efficiency, but from an environmental point of view, this over-investment could turn out to be beneficial. In order to understand the overall social welfare implications, it is therefore necessary to take into account those external costs.

Muller et al. (2011) present a method to estimate the external costs of air pollution in the framework of the national economic accounts. The suggested approach measures the gross external damages (GED) caused by each industry as the marginal external damages times the quantity of pollution at each source location. We estimate the external damages caused by CO2 emissions in Germany using different prices for this external damage following the recommendations of UBA (2019)and applying a sensitivity analysis.[22]

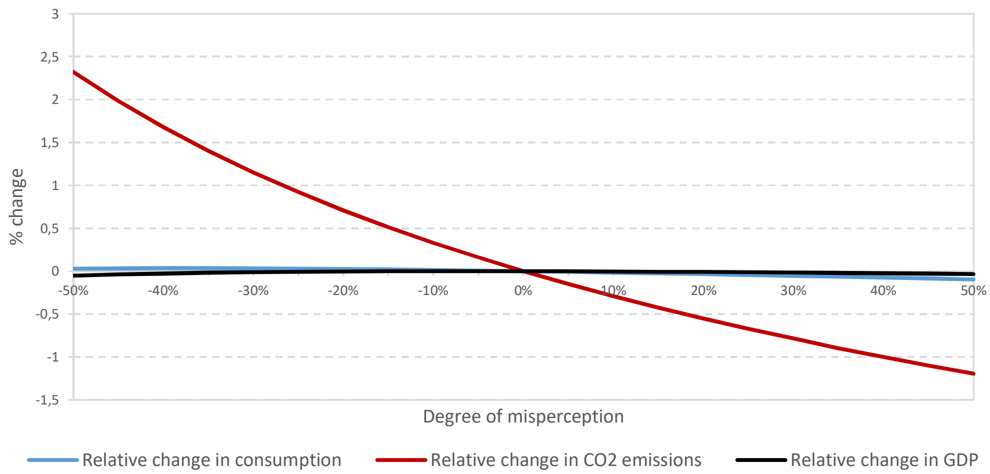
To calculate the social welfare impacts of changes in CO2 emissions we subtract the gross external damages from GDP. We are aware of the fact that the economy has many other existing distortions other than those from CO2 emissions and that following welfare results should therefore be interpreted with caution.

As the demand for electricity changes throughout the whole economy, also CO2 emission levels change. In the short-run (long-run), total CO2 emissions in Germany increase by 2.33% (4.96%) in case of a negative electricity price misperception of 50% and decrease by 1.19% (2.31%) when the electricity price is assumed to be 50% higher than it actually is. In the NMP scenario (PMP scenario), CO2 emissions that are caused by the electricity sector increase (decrease) by 4.59% (2.37%) in the short-run and increase (decrease) by 9.77% (4.56%) in the long-run.

Figure 16 displays the relative changes in consumption, GDP and CO2 emissions in Germany compared to a situation without a price misperception.

[22] As we do not model an emission trading scheme in our CGE model we do not estimate the net external damages, which equals GED minus the cost of pollution permits or any effluent charges.

Figure 16: Relative change in consumption, GDP and CO2 emissions in Germany



We can see that the change in energy service demand leads to very small changes in consumption compared to the benchmark situation without a misperception. However, the increased demand for electricity and production changes lead to an increase in total CO2 emissions in Germany, which is not accounted for in GDP.

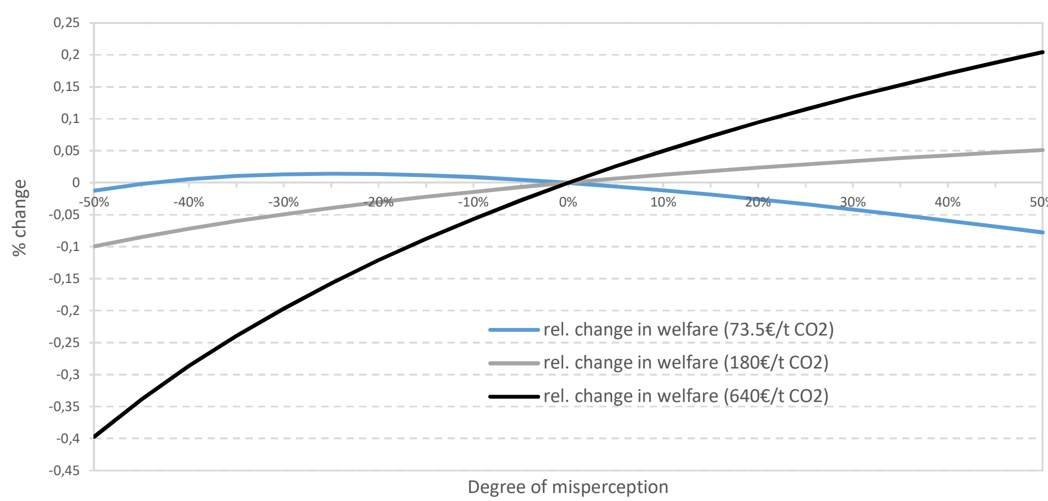
To see the impact of external damages from CO2 emissions, we apply different marginal external damages and subtract this damage value from GDP. However, to assign a price to a unit of CO2 emissions, it is necessary to make several assumptions, which have an impact on the level of the optimal price. Prices stated in the literature depend on a discount rate which makes economic effects comparable concerning the time dimension. A low discount rate values future damages relatively high (see for example Stern (2007)) while a high discount rate does the opposite (see for example Nordhaus (2007)). The optimal price for CO2 and other greenhouse gases is highly sensible to the assumed discount rate, especially if damages on the very long run are assessed.

The optimal price for CO2 further relies on implicit valuations of damages, which occur in countries with different income levels. The quantification of the economic damage of carbon emissions depends therefore on the question if a 1$ damage in a poor country is valued in the same way than a 1$ damage in a richer country. Moreover, we are confronted with a high level of uncertainty regarding the impact of carbon emission on the world climate and regarding the impact of the world climate on the economy, while the uncertainties tend to grow larger for long run developments (Tol, 2009). When the economic effects of climate change are evaluated, then it is possible that climate change affect the level of GDP in an economy and the potential of economic growth.

Tol (2009). finds a mean of 105$ (73.50€) per metric ton of carbon in a meta study. The German Environmental Federal Office recommends a cost rate of 180€/t CO2eq but also suggests a sensitivity analysis with a value of 640€/t CO2eq (UBA, 2019). Hepburn (2017) states that the optimal price for per ton of carbon may lie between 10$ and 1000$ per metric ton (8.55-855€) or above depending on the assumptions made regarding the aspects explained above.

To cope with the inherent uncertainty concerning the economic damage of carbon emission we display the results of our back of the envelope calculations for the above stated prices by UBA (2019)and Tol (2009).

Figure 17: Welfare analysis



We find that compared to the pure GDP analysis, the inclusion of external damage assumptions of CO2 changes a lot in our welfare analysis. A price of 180 and 640/t CO2eq ton increases the welfare effect of the price misperception considerably as it turns the negative price misperception in a welfare loss. Assuming a CO2 price of 640€/t CO2eq reduces welfare by 0.4% compared to a situation with no misperception.

However, we also see that a positive price misperception that leads to an overinvestment from a private perspective can turn out to be beneficial from an environmental point of view. Taking our upper bound price of 604€/t CO2eq, the reduced CO2 level that is due to the investment in more efficient technologies leads to a welfare increase of about 0.2%.

4. Conclusion

4.1 Conclusions empirical foundation MUSE

Behavioural factors affecting decision-making, resulting in heterogeneous choices across people, can affect the speed and dynamics of a transition to improved energy efficiency. Agent based models could be a very useful tool to address this diversity and choice interactions. There is however a great challenge to understand drivers of energy choice and identify the agents in ABMs, through which the empirical foundation could be improved. In this research, we address that challenge by starting with the data. A cross-country household electricity use dataset is combined with an in depth survey, collected during the PENNY project as well as the Cobham project, to identify consistent energy behaviours. To distinguish between household consumption and energy efficiency we have found a way of estimating energy service levels for household consumption characteristics. Based on cluster analysis methods we were able to partition a large population into groups with pretty strong demand-related characteristics, which formed the basis for deeper investigation into socio-demographical backgrounds, consumption and investment behaviour.

The clustering has shown that in terms of energy demand variables there is large distinction in energy consumption and efficiency levels between households, but the data does not allow us to recognise who these distinct groups are. There is a range of types of people (in terms of socio-demographic characteristics) that consume energy in very similar ways, in terms of energy efficiency and in terms of service level. There are, however, interesting patterns both between and within the clusters. Income, consistently, is the most pressing factor that affects demand, the relative efficiency gap, the dwelling efficiency, and investments. Other socio-demographic characteristics also have an effect – household size and to a certain extent age. Education does not have that important of a role, neither do environmental preferences, which are also not associated with being practical at saving energy or energy-literate. Clustering based on socio-demographic variables generates clusters that are not that different in investment behaviour, but clustering based on demand generates clusters that are different in investment behaviour. Investment comes from both inefficient and efficient groups, and is driven by income.

These results have been used to define the agents in the residential agent based model RSBM. There is a distinct difference between the technology uptake based on the original macroeconomic model and the empirical cluster based agents. In the macroeconomic case when a household reaches a certain income level it is assumed to adopt. In the cluster based analysis, however, socio-economic drivers are less distinct, as was also found in the data, and therefore the transition does not happen so swiftly. However, when the carbon price increases, and after some have adopted, a sudden shift can occur in a short time frame. The differentiation in household consumption (or service level) is found to affect the timing of adoption, as adoption of new technologies by some groups in that case can lead to a larger energy reduction that by others.

While this research demonstrates a modelling method, with a strong empirical grounding, it also shows that the complexity of choice dynamics is difficult to capture in distinct groups, which fit the ABM approach. Not being able to distinguish clear groups also makes it more difficult identify interactions. Therefore, systematic treatment of uncertainty in addition is required.

4.2 Conclusions building stock formulation EDGE

An improved understanding of final energy demand developments across different world regions was reached by involving building stock dynamics in the computation of regional U-values development over time. In developed countries, relatively low population and income growth will not foster high new construction rates and the currently existing building stock will as a result still hold a 75% share in 2050 in regions such as Europe. Therefore, renovation of the current building stock can have a big effect. When considering renovation investments, increasing insulation levels of opaque surfaces is generally convenient, while window replacement is rarely profitable and does not happen in the baseline estimations.

Conversely, high population and income growth in developing countries will lead to increasing shares of new buildings, as well as increasing floor space and a very strong cooling demand growth. Since, according to the new model results, developing countries still have to construct most of the building stock that will be standing in 2050, immediately implementing building codes can lead to significant energy demand reductions in the short and long term, given the long lifespan of buildings.

Useful energy demand is expected to slightly decline in a baseline scenario in Europe, due to the construction of highly efficient buildings and renovation of oldest vintages, with around 80% of the 2050 energy demand still attributable to the currently existing buildings. Renovation will be less impacting in the USA, but higher levels of demolition will be implemented in this region. In this scenario 50% of the 2050 energy demand will be attributable to new construction buildings. This holds true for China as well, which is expected to show an eight-fold increase in useful energy demand from 2015 to 2050, becoming the highest energy consumer region in the world. Renovation mechanisms will not strongly decrease energy demand in this country, due to the very low share of pre-1980 vintages in the future building stock.

Developing countries will generally show very low levels of useful energy demand, until they start increasing their cooling demand due to rising income levels. The new EDEG model shows that 75-80% of their 2050 building stock will be constituted by new buildings. At the global level, heating energy demand will slightly increase, while cooling will show a 10fold growth from 2015 to 2050, mostly due to China, middle and low income countries. In terms of final energy, increasing levels of equipment efficiency will eventually make the overall heating demand decline, while a huge growth in cooling demand will happen in any case. This eventually results in a 60% increase in final energy demand compared to 2015 level.

4.3 Conclusions price misperception simulations WIOD CGE

This report extends the analysis of households' energy service consumption by simulating electricity price misperceptions and behavioural inefficiencies in a CGE model. We conclude that the impact of potential policies aimed at increasing households' energy efficiency will crucially depend on whether households actually observe prices in an unbiased fashion. Our simulations further indicate that households' ability to process information and modify their expenditure structure accordingly is a decisive factor for the success of efficiency improvements in their homes.

We find that misperceived electricity prices change the way energy services are consumed but do not affect its overall consumption level by much. With respect to the rest of the economy in Germany and the EU, changes in production as well as consumption remain rather small for those goods that are only indirectly affected by the misperception of electricity prices. Confronted with the real market price, energy efficiency will increase when households perceived the electricity price to be lower than it actually is. Providing information on electricity prices can therefore

have a positive effect on electricity demand reductions if households are able to identify possible trade-offs in their energy service consumption.
Households that are aware of alternative and more efficient electric appliances can reduce electricity consumption by switching to more efficient technologies. We further show in our behavioural efficiency simulations, that improving the knowledge on how to save energy using appliances more efficiently has a greater effect in the short-run. If households are able to adjust their behavioural efficiency in energy service consumption over the long term they might refrain from buying more energy efficient technologies. As the electricity sector is mostly affected by the price misperceptions and behavioural inefficiencies of households, electricity production levels and CO2 emissions are also higher if prices are perceived to be lower than they actually are.

These results also hold true if households are able and willing to shift their consumption from energy services to other consumption goods or vice versa. The sensitivity analysis shows that when we relax the Leontief assumption in the consumer's utility function and allow for substitution across goods in consumption, the effect on electricity demand levels and CO2 emissions increases in magnitude. In the case of electricity price misperceptions, allowing for substitution in consumption reverses the effects of electric appliance purchases and other consumption as households increase energy service consumption in the case of negative price misperceptions.

However, when consumers perceive the electricity price to be higher than it actually is, providing actual cost information can turn out to be counterproductive in terms of energy demand reductions and CO2 emissions as households might realise that they pay less than they expected. Therefore, from a private perspective, households might invest too much in energy efficiency, but from an environmental point of view this over-investment could be beneficial. Potential co-benefits that result from reduced energy demand like health benefits trough better air quality will additionally have economy-wide implications. Our back of the envelope calculations showed that including different prices for CO2 and thereby analysing different damage assumptions is very important to when doing a welfare analysis as the investments in energy efficient technology above the cost-effective level can turn out to be welfare improving.

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