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Reducing Swiss household energy demand

Modelling and assessing non-monetary incentives (information and social norms)

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Zusammenfassung

In diesem Projekt untersuchen wir welchen Einfluss soziale Normen und Informationen auf die Energienutzung von Haushalten haben, wobei wir die Heterogenität von Haushalten besonders berücksichtigen. Zu diesem Zweck nutzen wir Befragungsdaten, die im Rahmen des SCCER CREST erhoben werden (SHEDS Daten) und entwickeln ein agenten-basiertes Modell. Dieses Modell beinhaltet unterschiedliche Typen von miteinander interagierenden Haushalten und ermöglicht es damit, individuelle Effekte konsistent zu aggregieren und auf Haushaltstypen zugeschnittene Interventionen zu analysieren. Bis jetzt haben wir die allgemeine Analyse der Befragungsdaten abgeschlossen, sowie die spezifische Auswertung der Elektrizitäts- und Mobilitätsteile vorangetrieben; wir haben ein Experiment designt und analysiert, um zusätzliche Daten zu gewinnen; und wir haben für Elektrizität, Wärme und Mobilität ein agentenbasiertes Modell aufsetzen können, welches detaillierte Prozesse für die Diffusion von Informationen und Normen beinhaltet. Unsere bisherigen Ergebnisse zeigen, dass soziale Normen und Informationen individuelles Verhalten im Energiebereich beeinflussen, sowohl in Bezug auf Investitions- als auch auf Nutzungsverhalten und dass Interaktionen mit Preissignalen teilweise wichtig sind. Allerdings bestehen erhebliche Unterschiede im Einfluss sozialer Normen und Informationen für verschiedene Arten der Energienutzung (Wärme, Strom, Mobilität) und für verschiedene Haushaltstypen. Somit scheint die grundlegende Idee des Projekts – die Analyse von Interventionen, die auf Haushaltstypen und Arten der Energienutzung abgestimmt sind – hochgradig relevant zu sein.

Résumé

Dans ce projet, nous étudions l’influence des normes sociales et de l’information sur l’utilisation de l’énergie par les ménages, en mettant un accent particulier sur l’hétérogénéité des ménages. À cet effet, nous utilisons des données d’enquête collectées dans le cadre du SCCER CREST (données SHEDS) et développons un modèle multi-agents couvrant différents types de ménages en interaction afin de pouvoir agréger de manière cohérente les effets individuels et d’évaluer les effets d’interventions politiques adaptées. Jusqu'à présent, nous avons terminé l'analyse générale des données de l'enquête, élaboré et analysé une expérimentation des choix (choice experiment) pour obtenir des données supplémentaires et développé trois prototypes du modèle multi-agents (électricité, chauffage et mobilité) ainsi qu'un modèle de diffusion de l'information. Les résultats obtenus jusqu’à présent montrent que les normes sociales et l’information influent sur les comportements individuels liés à l’énergie, tant en ce qui concerne les investissements que l’utilisation, et ont parfois des interactions avec des incitations de prix. L'influence des normes sociales et l’information varie fortement selon les types d'utilisation de l'énergie (chauffage, électricité, mobilité) et varie selon les types de ménage. Ainsi, l'idée principale du projet, l'évaluation des interventions adaptées aux types de ménages et aux types d'utilisation de l'énergie, semble être très pertinente.

Summary

In this project, we investigate the influence of social norms and information on household energy use with a particular focus on household heterogeneity. To this end, we use survey data collected in the context of the SCCER CREST (SHEDS data) and develop an agent-based model covering different types of interacting households for being able to consistently aggregate individual effects and for assessing the effects of tailored policy interventions. So far, we have completed the general analysis of the survey data, designed and analyzed a choice experiment to gain additional data, and developed three versions of the agent-based model (electricity, heat, and mobility) as well as a model of information diffusion. Results so far show that social norms and information influence individual energy-related behavior, both with regard to investments and with regard to usage and interact to some extend with price incentives. The influence of social norms and information varies strongly for different types of energy use (heating, electricity, mobility) and differs between household types. Thus, the main idea of the project, the assessment of interventions tailored to specific types of households and types of energy use, appears to be highly relevant.

Contents

Abbreviations

ABM – Agent-based model

EA – Electrical appliance

EEA – Energy-efficient appliance

ElCom – Federal Electricity Commission

FEDRO – Federal Roads Office

FSO – Federal Statistical Office

GA – General Abonnement

HTA – Half Fare Travelcard

MoT – Mode of Transport

RA – Regional Abonnement

SBB – Schweizerische Bundesbahnen

SFOE – Swiss Federal Office of Energy

SHEDS – Swiss Household Energy Demand Survey

1 Introduction

1.1 Background information and current situation

Reducing energy demand is central to achieve the Swiss Energy Strategy 2050 targets. To achieve a reduction of energy consumption per capita, influencing household energy demand will be important, as households decide about a substantial part of residential and mobility-related energy use (about 2/3 of final Swiss energy consumption). Household behavior can be influenced by monetary incentives but also by individuals' information levels, perceptions of, and responsiveness to social norms. These so-called "soft incentives" could be crucial for improving energy efficiency (Alcott, 2011).

Two important aspects need to be considered when focusing on soft incentives: (1) the aggregate effects and (2) tailored interventions that are specific to types of households or types of energy use. To do that, two connected tasks are essential: (a) assessing the effects of soft incentives on behavior and on the performance of monetary instruments on the household level and (b) aggregating these effects to the national level. Both are non-trivial tasks that require substantial research.

On the household level, most of the existing empirical research focuses on monetary incentives (see, for example, Alberini et al., 2013; Alberini and Bareit, 2016; or Bruderer et al., 2015). Studies on non-monetary incentives usually focus on specific measures and thus provide rather fragmented information (e.g., Goldstein et al., 2008; Griskevicius et al., 2010; or Degen et al., 2013). Furthermore, results from the Swiss Household Energy Data Survey (SHEDS) suggest that there is substantial heterogeneity among household types and among different types of energy use that could be (but, so far, has not been) used to tailor soft incentives to particular groups or types of energy use.

On the aggregate level, assessing total effects of soft incentives requires novel tools, as these incentives are based on interactions among households (social norm formation, information diffusion). An assessment of aggregate effects requires tools that capture not only the effects of information and social norms on household behavior but also describe how changes in behavior or policy measures influence such norms and the availability of information. Currently, such tools do not exist.

1.2 Purpose of the project

In this project, we provide a model-based assessment of the aggregate effects of social norms and information on energy use (in the domains of mobility, electricity demand and space heat) that takes into account different types of households (population segments) and their interactions and that is based on a detailed empirical assessment of the effects of social norms and information on the individual level.

On the individual level, we use survey data to analyze the relation between energy literacy and the responsiveness to social norms and detailed measures of energy use (in the aforementioned domains) for different types of households. On the aggregate level, an agent-based model is developed that uses the empirical results to describe and aggregate individual behavior, taking into account feedback effects from changes to social norms and information diffusion. Finally, both the empirical and the model-based analysis will be crosschecked with a different data source (municipal data) for mobility and electricity usage.

The project is embedded in SCCER CREST and helps to advance its research line on the transfer of insights on consumer behavior into the design, modeling, and evaluation of energy polices and regulations. It also complements the development of a detailed demand-side model within CREST. The project utilizes the basic structure of the model developed in CREST (description of different types of energy use and different types of households) but extends it to cover information and social norms in addition to the standard policies (such as prices) that is part of the basic CREST model.

1.3 Objectives

In detail, we first investigate (based on survey data) how strongly perceived pressure from social norms, energy literacy, and energy prices influence energy-related behaviour and whether these influences differ among different socio-demographic groups (clusters[1]). We expect to see different levels of influence between clusters, which would indicate that there might be a benefit of tailoring policy interventions to particular subgroups of the Swiss population (e.g., using norm-based campaigns for rural areas and information-based campaigns for urban areas).

Second, we use this analysis to build a model that captures feedback effects (such as changing social norms or a diffusion of information in networks). This enables us to simulate aggregate effects of policy interventions. We expect to be able to show that a) tailoring policies becomes even more advantageous in an aggregate setting, as non-targeted groups will be influenced via such feedback effects by targeted groups; and b) that aggregate effects differ substantially from upscaled individual effects, indicating that a dynamic model is indeed essential to assess aggregate outcomes.

Finally, we will use a second data source to cross check our findings and will provide a simplified model version for use in other simulation models.

[1]We distinguish five household segments according to the place of living and the age group of adult household members. Cluster 1 subsumes the young urban population, cluster 2 the young rural, cluster 3 are the middle-aged urban households, cluster 4 the middle-aged rural, and cluster 5 are the seniors (urban and rural).

2 Procedures and methodology

The project consists of two parallel streams. Workstream 1 “Empirical Analysis” analyses the influence of information and social norms on different types of energy use for different types of households, using the CREST household survey SHEDS as well as municipal data on mobility and electricity use. Workstream 2 “Agent-based modelling” develops an agent-based model of energy consumption of different household types and of the interactions stemming from information diffusion and the formation of social norms. The empirical insights resulting from the analysis of SHEDS are used to initialize and calibrate the agent-based model. Also, municipal data that is gathered in Workstream 1 will serve as validation for the model predictions.

In 2020 the main focus has been on WS 2 and the development of the model framework as well as deriving the needed data and insights on the municipality level for the models.

2.1 Workstream 1 “Empirical Analysis”

The empirical analysis consists of two steps. In Task 1.1 “Information and Social Norms”, survey data is used to analyse the influence of social norms and information on individual energy use (electricity, heating, mobility) for different clusters of households (five population segments by age and the place of living). Task 1.2 combines additional survey data and municipal data for a more detailed analysis of energy-relevant behaviour in the three sectors. It also includes the discrete choice experiment (see below).[2]

Task 1.1 has been completed. Within Task 1.2, we will analyse one final wave of SHEDS to corroborate our understanding of the relation between soft incentives and energy demand behaviour. Additionally, we implemented a randomized controlled discrete choice experiment to have an additional source of data. In 2019, we conducted the experiment to test two soft-measure treatments in the situation of a home relocation. With a home relocation as the choice setting, we can gain insights into the decision-making process, when choices have a potentially large impact on the future energy consumption of a household. By choosing a home with energy conserving characteristics, a path for the energy consumption related to that home is set. The size of the living space, the energy efficiency and the location of a home lock in a substantial share of a household’s energy demand. The larger the living space the more heating is required. An energy efficient home, which is built according to a high standard with regard to energy efficiency (e.g. Minergie), consumes ceteris paribus less energy than a home with a low standard. These two characteristics cover important aspects of electricity and heating demand of a home. A third housing-related aspect that affects energy demand for mobility is the location of the home. The distance between the home and places that are visited on a regular basis, such as work or caretaker responsibilities, influences the energy required for such trips independently of the chosen mode of transport.

As such relocations occur too rarely to be readily observable in a mid-scale survey, such as SHEDS, a different method was necessary. We designed a choice experiment that places respondents in a fictive relocation situation and included several treatments to analyze how the relocation decision might be influenced by the soft measures considered in this project. The experiment was designed in collaboration with other CREST researchers (see Annual Report 2019). The results of the experiment are presented in Section 3.1.

[2] Note that originally Workstream 1 consisted of three tasks. When extending the timeline to the end of 2021 last year, we merged Tasks 1.2 and 1.3. For more information, see Fig. 10 in Section 5.

Regarding the municipality assessment Task 1.2 aims to complement the SHEDS insights by focusing on energy relevant data structures on the local level and relate this to socio-economic indicators. To this end we have collected three types of data: (i) socio-demographic and economic characteristics, (ii) mobility behavior, and (iii) proxies for social norms and information. For heating and electricity, we were not able to find sufficient locally differentiated data.

As detailed individual information is not available in the municipal data, one of the challenges is to find appropriate proxies for social norms and information.[3] Regarding social norms at the municipal level, we have considered the following proxies: Environmental ballots (Energy Law: LEne), vote for Green Party during the national election, Green Business (organic bread) in Migros shops. As a proxy for information (energy literacy), we have information on LED light bulbs in Migros shops. The mobility data includes information on both public and private transports. More precisely, we use the following variables: GA per 1000, HTA per 1000, Total cars per 1000, Share of clean e-car, Share of car efficiency type A, Share of car efficiency type G, and Share of dirty hybrid.

Using the municipality characteristics regarding age distribution and typology, we apply the same manual clustering approach as in the previous analysis on the SHEDS data. Here, the age distribution is based on the dominant group and when the percentage is higher than the mean of the full sample. This is consistent with the age distribution in SHEDS data (see Table 1). For the segmentation, we cross this age distribution with city typology to get five clusters. This cluster distribution is also consistent with the one in the SHEDS data analysis (see Table 2).

Table 1: Age distribution based on dominant group and percentage higher than the mean of the full sample.

	SHEDS		Municipality	
	Number	Percent	Number	Percent
20-39	7,823	39.22	895	36
40-64	9,025	45.24	1,234	49
65+	3,100	15.54	365	15
Total	19,948	100	2,494	100

Table 2: Clustering (Urban and Intermediate together).

	SHEDS		Municipality	
	Number	Percent	Number	Percent
20-39 and Urban/Intermediate	4,495	22.53	636	25.55
20-39 and Rural	3,328	16.68	259	10.41
40-64 and Urban/Intermediate	4,002	20.06	521	20.93
40-64 and Rural	5,023	25.18	708	28.45
65+	3,100	15.54	365	14.66
Total	19,948	100	2,489	100

[3] The socio-demographic data provides sufficient detail for control variables on aggregated level (i.e. canton, size of the population, density, age distribution, income, size and number of households, city typology, employment).

2.2 Workstream 2 “Agent-based modelling”

The model-based analysis in Workstream 2 consists of designing a model that is capable to describe the behaviour of consumer agents who are influenced by social norms, information and policy interventions. To this end, an agent-based model has been designed that captures the basic investment and usage decisions with respect to electricity, heat and mobility. Following, we will briefly describe the basic model structure as well as the specific sectoral aspects.

2.2.1 Overarching model structure

The agent-based model approach is designed to account for the relevant decision aspects for investments and usage of energy applications of households and the potential interaction among households. To this end the three agent-based models for electricity, heat and mobility are developed that follow the same basic structure (Figure 1).

Each model starts with the initialization and parameterization of the agent population (households). The initialization is performed once, so that it does not change in the following simulation. The simulation determines the iterative decision processes of the agents from period to period. An arbitrary number of iterations can be simulated where one iteration corresponds to one year. After the simulation, the results are reported in different resolutions as well as validated and calibrated.

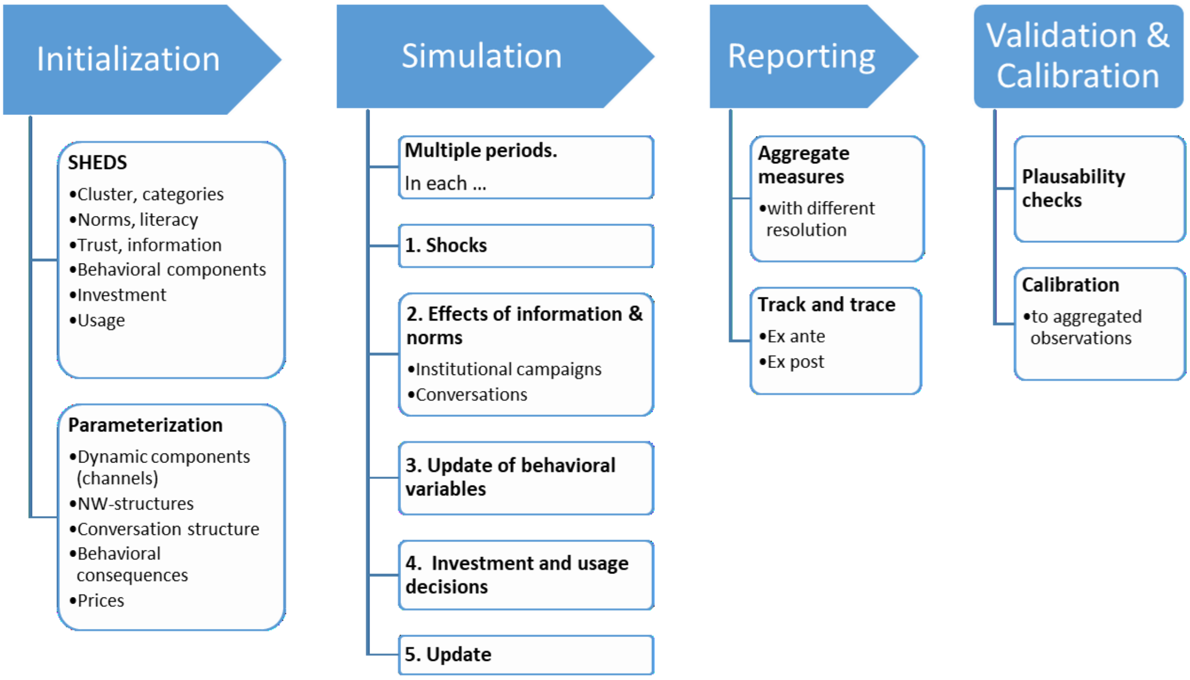

Figure 1: Basic structure of the agent-based models.

Initialization

The agent population of the models is based on the Swiss Household Energy Demand Survey (SHEDS) providing detailed information on consumption and usage decisions for electricity, mobility and heat.[4] Agents in the agent-based model (ABM) mimic the SHEDS population whenever possible. They are segmented into five clusters according to age and location (see details in section on electricity ABM). In addition, households are further subdivided into categories based on socio-demographic characteristics

[4] For more information on the SHEDS, see, e.g., https://www.sccer-crest.ch/research/swiss-household-energy-demand-survey-sheds.

(such as household size). Whereas the cluster definition remains unchanged across all three models, the categorization may change depending on the individual models (see section on specific ABMs). From SHEDS, each agent is assigned character traits such as perceived pressure to meet social norms (descriptive and injunctive) or energy literacy as well as possible information channels (family, neighborhood, SFOE and utility) and trust in the respective channel. Furthermore, each agent is assigned model-specific behavioral variables (such as preferences) as well as investment and usage variables, which can change in later simulations.

Data from SHEDS are imported into the model, either as conditional probabilities for each subgroup (e.g. clusters) in the case of categorical variables or as distributions for continuous variables. When significant correlations are observed in SHEDS, we consider correlations for behavioral, investment, and utilization variables with an agent's cluster and any combination of injunctive and descriptive normative pressure and literacy levels. Otherwise, we use the observed SHEDS data.

In the further initialization phase of the model, the dynamic components (such as channels for institutional campaigns) and networks are built up in which the agents are connected to each other. To this end, family, friend and neighborhood networks are considered (Figure 2). Whereas the family network is not determined by the age and location of the agents, the age of the agents is taken into account when forming the network of friends and the location of the agent is taken into account when forming a neighborhood network. A further segmentation, for example according to social norms, trust, and literacy in the formation of networks can be activated.

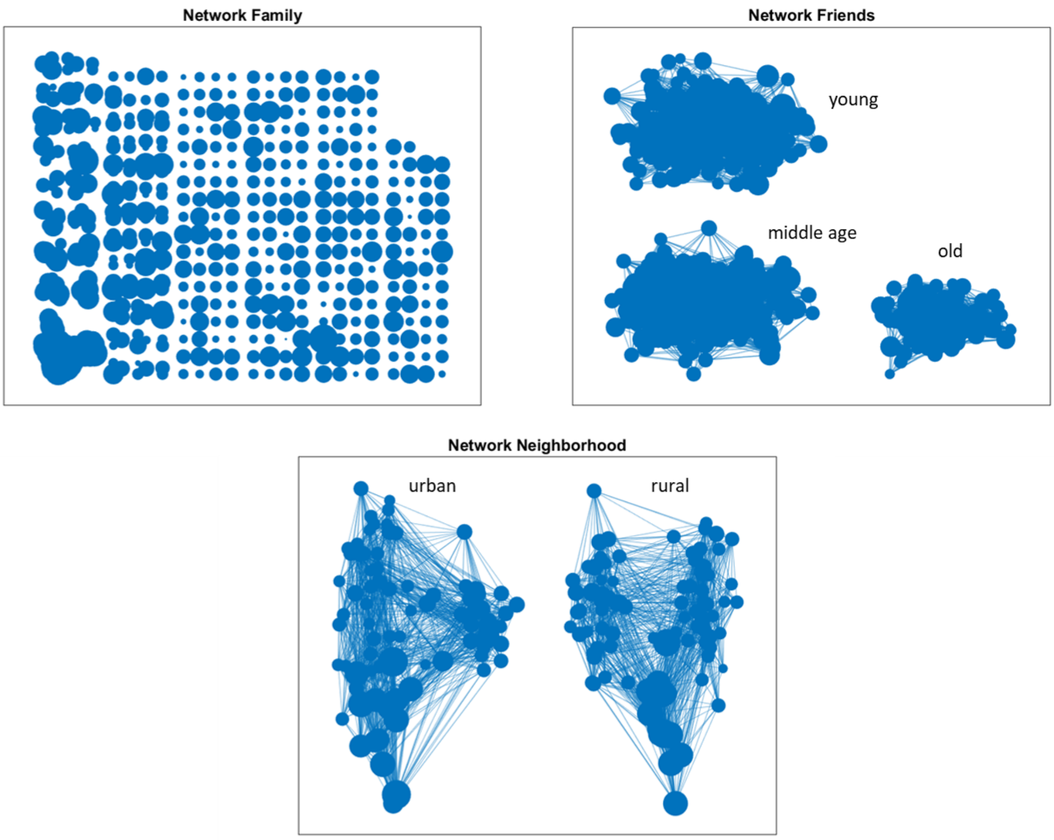

Figure 2: Family, Friends and Neighborhood networks of agents.

In addition to the networks, the conversation structures are established. These can be flexibly adapted in the simulations (see next section). In the last step of the initialization the behavior consequences are defined (e.g. influence of prices on the preferences of the agents). As no data from SHEDS is available for this and other parameters such as prices, these are taken from corresponding literature and external data sources.

Simulation

After the initialization, the iterative decision processes of the agents for multiple periods is simulated. The simulations have a predefined sequence and individual channels and modules can be activated or deactivated (including shocks – like a price shock – at pre-defined periods).

In all simulations, we differentiate between behavioral variables that describe what the agents wants to do (e.g., the share of efficient appliances a household wants to own) and the actual decisions of an agent (e.g., whether an agent replaces an appliance by an efficient or non-efficient one). This distinction enables us to include of random deviations from planned behavior, which is essential to maintain a heterogeneous agent population in the model.

At the beginning of every simulation period, we allow for campaigns from different institutions (SFOE, local utility) that can produce either injunctive or descriptive norm pressure. These can, in turn, trigger changes to the behavioral variables of the different agents. After the campaigns, conversations between agents take place. We allow for different setups of conversations (i.e. with respect to matching conversation partners, conversation sequence, design of each conversation (topic, direction of influence) and the effect of the conversation (size of influence).

Depending on the specification of the campaigns and the conversations, both household characteristics (e.g., the level of knowledge) and their behavioral variables can be influenced. In addition, the behavioral variables are also influenced by prices and costs (or other aspects, such as rebound effects). With regard to prices, price-elasticities are included in the models. Regarding costs, the relative life cycle costs (investment and operating costs) of two alternatives are compared by the agents. Here the agents weigh the investment and operating costs differently, depending on whether a household is budget-constrained or not (a budget-constrained household will give a higher weight to present expenses, such as investment costs, compare to future expenses, such as operating costs). All these changes to the behavioral variables can be activated or deactivated at the beginning of the simulation to facilitate a detailed investigation of what influences agent behavior.

After the update of the behavioral variables, the agents make their investment and usage decisions. Thereby the investment and usage decisions are interlinked (one can influence the other). Before the next period is simulated, all stock variables that have changed are updated (e.g., number of appliances owned by an agent).

Reporting

At the end of the simulation, the results are visualized and summary statistics are generated. Aggregated measures (like mean values or distributions) with different resolution (cluster or category level or sub-populations) can be reported. Furthermore, individual agents can be tracked and traced (ex-ante or ex-post).

Validation and calibration

The results of the simulations are finally validated and calibrated. The validation includes plausibility checks by comparing the direction and size of the simulated changes to findings in literature. The calibration is also based on a comparison with literature or previous studies in the respective sectors. In addition, the municipality data collected in Workstream 1 will be used to verify and adjust the spatial differences in the agent-based model with the observations for Switzerland. Since the municipality data are only available for mobility, they can only be used to a limited extent for electricity and heating.

2.2.2 Electricity

The electricity ABM acts as the main blueprint for the heating and mobility models. In the following, we will provide the more general aspects- in particular on household structures – as well as the specific electricity related aspects.

Specification

The ABM on electricity simulates the electricity usage of agents from electrical appliances (EA). EAs include all large electrical appliances in households (refrigerator, freezer, dishwasher, dryer and television) that have a label. Based on the label, energy-efficient appliances (EEAs) can be identified. The sample of the electricity model includes about 15'000 households from SHEDS (from all SHEDS waves except the last one). The segmentation of the households into the five clusters is shown in Table 3.

Table 3: Sample of electricity model.

	Definition	Number of HHs/ Agents
Cluster 1	young city	3407
Cluster 2	young agglo & country	2428
Cluster 3	middleold city	3015
Cluster 4	middleold agglo & country	3777
Cluster 5	old city & agglo & country	2334
Total		14961

This basic household clustering is also applied for the heating and mobility models. The households are further subdivided into eight categories based on the following socio-demographic characteristics:

- Household size
    - Small vs large (> 2 persons)
- Tenant status
    - Renter vs owner
- Income
    - Not poor vs poor (income <4500 gross CHF/month)

In the initialization the average electricity usage is 2200 kWh/a, the average number of EAs is 5, while the average EEA number is 3. The *"preferred EEA share"* is created from the observed EEA share (i.e. EEA number/ EA number), but corrected for the fact that the labels were introduced relatively recently. Due to this effect, the observed share of an agent can still be lower than its preferred share. On the usage side, the "*effort"* is defined as the behavioral variable of each household. In the initialization, this effort level is derived from a SHEDS question on the electricity saving plans of individual households. As mentioned in the previous section, the behavioral variables can be influenced in the simulation phase by norms and information channels such as conversations, network effects or institutional campaigns, but also by price changes. Both the preferred share of EEAs and the efforts of households to reduce their electricity consumption determine the decisions of agents in subsequent periods when buying new appliances (investment stage) or determining the usage level (usage stage).

Investment

In the investment decision stage the actual change of the EA stock takes place; i.e., the decisions on new as well as the replacement of broken appliances. We allow different replacement cycles for tenants and owners (e.g., replace 1:1 vs more at once) as well as bulk or individual replacement. Independent from replacement, the overall EA stock can also be increased or decreased (down to a minimum stock). The decision what type of appliance is purchased (energy-efficient or non-energy-efficient) by the agent is defined by its preferred share (i.e. the preferred share represents the buying probability for EEAs).

As budget constraints can be relevant for investment decisions, we limit poor households whose budget is constrained to replace appliances only in case of failure and if the failed appliance was an essential one. If the appliance was essential, the budget-constrained household replaces the failed appliance with the cheapest option, taking into account only the purchase price (investment costs) and not the operating costs.

Usage

The investment decision has an influence on the usage level. On the one hand by changes in the stock of appliances, on the other hand by changes in the types of appliances (efficient or not). In the model, we represent the usage level of each agent by a production function including the number of efficient and inefficient appliances and the effort level. In addition, a calibration factor is included in the function that captures deviations in the calculated usage level and the observed usage level in SHEDS that are caused by factors not considered in the ABM, such as the exact number of persons in each household. The calibration factor is calculated in the initialization phase and kept constant thereafter.

2.2.3 Heating

Building upon the investment-usage structure of the electricity model, the heating model transfers this structure to the heating sector.

Specification

The heat sample is the same as the electricity sample, including the segmentation of households into clusters and categories (see section on electricity ABM). For the heating related decision we account for the following structural parameters as they influence investment decisions and thereby also usage:

- Accommodation size
  - Small
  - Large (> 140 m^2)
- Accommodation age
  - Old
  - Old, but renovated (windows only)
  - New (>= 1990 or renovation of at least windows and facade >= 1995)
- Heating system
  - Non-conventional (wood, heat pump, solar, district heating)
  - Conventional (oil, gas, electricity)

In the initialization the average heat energy usage is about 12500 kWh/a, 30% of households have a non-conventional heating system, while 30% live in a large accommodation. In terms of the age of accommodation, 20% live in an old accommodation, 15% in an old but renovated accommodation and 65% in a new accommodation.

As with the electricity model we use investment and usage related behavioural variables: the preferences of the agents for a heating technology, accommodation age and size are the variables on the investment side; the “effort” of households to reduce their heat usage is again used on the usage side. The effort level is based on a SHEDS question about the ventilation behaviour of households while the preferences for heating technology and the age of the accommodation are derived from the current state but are corrected by the fact that standards or labels (e.g. building standards) have only been introduced relatively recently. Regarding the size of the accommodations, we assume that the small households (<= 2 persons) also prefer smaller accommodations (in accordance with the observations in SHEDS).

Again, the behavioural variables can be influenced in the simulation phase by norms and information channels such as conversations, network effects or institutional campaigns, but also by price changes. The preferences and the effort of households to reduce their heating consumption determine the decisions of agents in subsequent periods when deciding to change their heating system or accommodation (investment stage) or determining the usage level (usage stage).

Investment

In the investment phase, the agents make their decisions about changing the heating system or accommodation. A distinction is made here between renters and owners. Renters decide only on their accommodation and the respective age and size, but not on the heating system, as this is given for renters. The owners decide on the heating system and the age of the accommodation, but not on the size of the accommodation (which is assumed to be fixed in our setup). With regard to the age of the building, we only consider minor renovations, since major modifications to the building would not be profitable in the time horizon considered in our simulations. This implies that owners who own an old building can only change the building age to "old but renovated", but not to "new".

Since changes in the heating system or the accommodation do not occur at regular intervals, we currently assume that renters change their accommodation at most every five years and owners change the heating system or renovate the building at most every 20 years. As far as heating is concerned, however, there is the possibility of a failure and we assume that the probability of a failure increases with the age of the heating system.

The income situation of households is taken into account in the investment decision in a simplified manner. Poor households that are budget constrained in a period do not change their accommodation situation. Regarding the heating system, owners who are budget constrained only make changes when the heating system fails. In this case, they choose the cheapest alternative (based on the investment cost).

Usage

Again similar to the electricity model, the agents' investment decisions have an impact on their usage levels. The usage level is defined by the heating system and the respective basic consumption of the system, the size of the accommodation, a mark-up for old buildings and the efforts of households to reduce their energy consumption. The calibration factor captures factors that are not considered in the model (e.g. the precise household size). As a mark-up for the accommodation age we currently assume 0.8 for old buildings and 0.4 for old but renovated buildings compared to new buildings (Gerster and Nietlisbach, 2014; SFOE, 2007).

2.2.4 Mobility

Contrary to the electricity and heating model, the mobility ABM needs to account for the fact that transport related decisions are taking place on an individual level and consequently can differ for the individual members of a household.

Specification

We use a rather simplified mobility representation and focus on the distinction between private and public transport. On the investment side, the decision variable is the stock of private and public means of transport of the agents. For private means of transport (cars), electric cars are also considered. However, as we do not have information on the number of electric cars in SHEDS, but only on their availability, this measure is used as a further decision variable.[5] On the usage side, our decision variable is the mode of transportation (MoT), differentiated by work and leisure time. In contrast to the other two models, it is important to distinguish between variables at household level (i.e. means of transport stock) and those at individual level (i.e. MoT).

Accordingly, in the simulations on mobility, usage decisions are made at the individual level, but investment decisions are made at the household level. As the SHEDS data only contain information of the respective respondent regarding the MoT (and also the commuting distance), we generate artificial households in the initialization stage. We make sure that the individuals of a household are always drawn from the same pool (regarding norms, literacy and cluster), but the MoT (and the commuting distance) within a household can still be different.

The sample for mobility from SHEDS is smaller than that for electricity and heating. In total, the sample consists of 6395 households and 15196 individuals (the average household size is about 2). We keep the same cluster definition as in the other models. The households further subdivided into ten categories based on the following socio-demographic characteristics:

- Household size
  - One person vs two or more persons in a household
- Workers
  - No vs one vs two or more workers in a household
- Income
  - Not rich vs rich (income >9000 gross CHF/month)

In the initialization, about 70% of households have at least one car, but also at least one ticket for public transportation (regional or general abonnement). Of those households that have at least one car, about 6% have an electric car. In terms of commuting distance to work (available only for work), 40% of the individuals have no commuting distance (less than 1 km), 20% have a short distance of less than 10 km, 30% have a medium distance between 10 and 50 km and 10% have a long distance of more than 50 km. Regarding MoT at the household level, 45% use public transport to get to work (all persons in these households use public transport), 30% use private transport and the rest use both private and public transport. In leisure time, 40% of households use only private transport as MoT, 20% use public transport and the rest use mixed (public and private) transport.

[5] Soft mobility is not considered further, as this is only a limited active decision (e.g. more defined by the proximity of the place of residence to the workplace).

As in the other models, we use behavioral variables for usage and investment. In the mobility model, the behavioral variables represent preferences for the MoT (at individual level) and for the transport portfolio (at household level). Details are described in the next sections.

Investment

We rely on an estimation function based on the SHEDS data, to identify the preference for the preference of a household for its private (public) transportation stock. In the investment phase, we use an OLS function with the stock of private (or public) transport as dependent variable and MoT (for work and leisure), norms and literacy as independent variables with further consideration of control variables. The residual of this estimation is defined as preference variable that can be influences by the model's conversation and campaign structure. Similar, if in the simulations the MoT, norms, literacy level of a household change, its stock of private (public) transport can change as well. However, as with electricity and heating the respective investments are not carried out each year.

For households that have a car, we also use an estimate of the probability of having an electric car. Therefore, we estimated a logit model (and implemented it in ABM) with the probability of having an electric car as a dependent variable and the cost of an electric car, norms and literacy as independent variables. As in the previous estimations, other control variables are considered and the residual value is interpreted as households' preference for electric cars.

Usage

On the usage side, we used the same procedure as with the investments, by transferring the estimation function for the SHEDS data to the ABM. For usage, we use a logit model with the probability that the MoT is public transportation as dependent variable, and the norms and literacy as independent variables, taking into account further control variables and interpreting the residual as preference for the MoT. In comparison to the investment decision, the usage decision is made on an individual level. For work and leisure time separate functions are estimated and implemented, whereas the function for work additionally considers the commuting distance (not available for leisure time). If in the simulations, the norms, literacy levels or preferences (residuals) change, the individuals make changes in their MoT (but not immediately after every small change).

3 Activities and results

In 2020, Workstream 1 has focused on extending the municipality analysis and finalizing the choice experiment examination (the analysis of the 5th wave of SHEDS had to be delayed due to the late running of the survey because of the COVID-19 pandemic). The ABM of Workstream 2 has been finalized and first model test showcase the important channels and parameters that need to be accounted in the scenario assessment. The full scenario simulations are scheduled to be finalized in 2021.

3.1 Workstream 1 "Empirical Analysis"

To learn more about the influence of soft measures on the home relocation decision we implemented and analysed a discrete choice experiment. For the experiment, returning survey participants were randomly assigned to one of two soft incentive treatment groups or a control group. One group received a social norms treatment, which conveyed descriptive as well as injunctive norms. The normative message indicated what housing characteristics others have generally chosen as well as which choices are socially approved of. Another experiment group received an information treatment, which notified participants of potential future cost savings through the choice of housing with energy-conserving properties. A third experiment group acted as the control group and only received the general introduction common to all groups.

As we are interested in behavioural differences across household types in reaction to the treatments, we segmented households according to our segmentation strategy defined in the Annual Report 2018. We distinguish five household segments. Two segments describe households in the 20 to 39 age bracket living in either urban or rural areas. Two more segments include households aged 40 up to 64 in urban or rural areas. The final segment summarizes senior households (age 65 and more). Each of our five household types is well represented in the sample with at least 50 respondents within each control and treatment group.

We have used mixed logit models for the full sample as well as for each household segment individually in order to investigate treatment effect heterogeneity. The results suggest that soft measures mostly affect the relocation decision through the choice of the living space size in our setting. For the full sample, we find social norms to incentivize the downsizing of the accommodation. This effect is illustrated in Figure 3, which depicts the predicted choice probability of an increase of the living space at various levels of the current per person accommodation size in square meters. The effect is stronger, the more space household members currently can take up in their home. Given that these households deviate most from the norm-conform living space size that was conveyed in the treatment, this observation is line with our expectation.

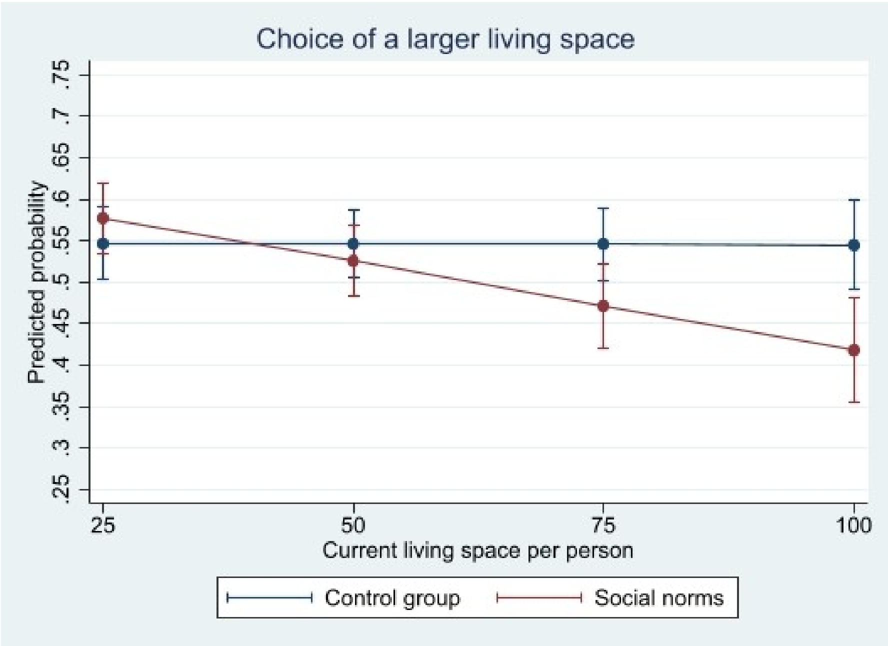

Figure 3: Predicted choice probability for a larger than currently inhabited living space for the full sample.

However, the full sample results overlook the complete impact of the treatments because they neglect the existence of different types of households. Hence, we uncover significant differences in treatment effects by turning to the household segments that we distinguish in the project. Segment-specific treatment effects tend to be stronger than what is deduced from the full sample results. Furthermore, the treatments elicit substantial reactions from some of the household types but are not effective with others. Young households in urban areas react to information and are less likely to choose housing with an increased living space size under treatment. Young households in rural areas on the other hand show no response to the two treatments when choosing the housing size. Amongst households in the middle age groups, we find treatments to be effective in rural areas but not in urban ones. Mid-age, rural households choose the size of the living space differently under the influence of social norms as well as information compared to the control group. Compared to the control group, social norms treated households in this segment are less likely to choose an increase of the accommodation size and are more likely to downsize the larger their current per person living space is. On the contrary, the information treatment has the undesired effect of leading to an increase of the living space for households living in large homes. It can only incentivize households with a currently small per person accommodation size to avoid the move to a larger home. Finally, senior households can be positively affected through social norms to reduce the probability of choosing a larger than the currently inhabited home.

Within the scope of a Master's thesis, our research assistant, Noëlle Fricker, provided some additional insights to our SHEDS analysis by investigating the behavioural consistency of low energy consumers across the three energy domains electricity, heating and mobility. Her results indicate that there are significantly positive correlations of energy consumption between the domains. Households, which are amongst the least electricity consuming ones, are also more likely to consume the least energy for heating and warm water. The extension of this observation to mobility behaviour is, however, only partially permissible. There is no significant consistency between low energy consumption for mobility and electricity. There is however consistency between the relative level of energy consumption for mobility and heating. The high electricity-consuming households are also more likely to be amongst the highest energy consumers for mobility purposes.[6]

Regarding our work with municipality mobility data, we have analyzed the data econometrically for the full sample and by cluster. The results for the full sample estimation are summarized in Table 4. They show that there is no good proxy for Social Norms (SN) that works for all the mobility decisions while the proxy for information works for all the decisions. We find that information has a significant and positive effect on public transport cards and the share of clean electric vehicles. On the contrary, information has a negative and significant effect on the number of cars in the municipality. This is consistent with the results that we have found at the household with the SHEDS data. Regarding the social norm, green business, environmental ballot, and green party vote have a negative and significant effect on the number of cars in the municipality. While their effects on public transport cards and clean electric vehicles are positive and significant, the green business proxy has no significant effects. We also find the same contradictory effects for the three proxies on the share of car efficiency type in the municipality. It seems reasonable to argue that proxies for social norms at the municipal level have different impacts on mobility decisions.

Table 5 summarizes the results for the cluster estimation. We find that Information (Inf) and Social Norms (SN) have different influences on the decisions across clusters. For example, information only significantly and positively affects public transport cards for cluster 1 (Young in the city), while social norm has negative and significant effects on the public transport card GA for cluster 2 (Young in the rural area). Regarding the private transport decision, information has a significant and negative effect only for Cluster 4 (Middle age in rural areas) while social norm has the same effect for Cluster 2 and Cluster 3 (Middle age in the city).

Table 4: Summary results: Full sample (N=2500).

	Information	Social Norm		
	LED	Green business	LEne	Green Party
GA per 1000	Yes(+)	**No**	Yes(+)	Yes (+)
HTA per 1000	Yes (+)	No	**Yes(+)**	**Yes(+)**
Total car per 1000	Yes(-)	Yes(-)	Yes(-)	Yes(-)
Share of clean e-car	Yes(+)	No	**Yes(+)**	**Yes(+)**
Share of car A	*No*	*Yes(-)*	*Yes(+)*	*Yes(+)*
Share of car G	*No*	*Yes(+)*	*Yes(-)*	*Yes(-)*
Share of dirty hybrid	*No*	*Yes(-)*	*Yes(+)*	*Yes(+)*

[6] Energy consumption for mobility was analysed based on mobility behaviour for leisure activities and flight behaviour.

Table 5: Summary results for the cluster estimation.

	1		2		3		4		5		All	
	Inf	SN	Inf	SN	Inf	SN	Inf	SN	Inf	SN	Inf	SN
GA	Yes(+)	No	No	Yes (-)	No	No	No	No	No	No	Yes(+)	No
HTA	Yes (+)	No	No	No	No	No	No	No	No	No	Yes(+)	No
Car	No	No	No	Yes(-)	No	Yes(-)	Yes(-)	No	No	No	Yes(-)	Yes(-)
Car A	No	Yes(+)	Yes(+)	Yes(-)	No	Yes(-)	Yes(+)	Yes(-)	No	No	No	Yes(-)
Car G	No	No	No	Yes(+)	No	Yes(+)	No	Yes(+)	No	No	No	Yes(+)
Clean e-car	No	No	No	No	No	No	Yes(+)	No	No	No	Yes(+)	No
Dirty hybrid	No	No	No	No	No	Yes(-)	Yes(+)	Yes(-)	No	No	No	Yes(-)

3.2 Workstream 2 “Agent-based modelling”

As the scenario simulations are not yet finished this chapter provides first results of exemplary simulations as illustrative examples. The simulations were carried out for the electricity model and the heat model, but not yet for the mobility model. A base case, a price shock scenario and a scenario for an exemplary institutional campaign were simulated (same scenarios for electricity and heat model).

Electricity: Persistent electricity price shock

In our base case, all channels are activated in the model, but the system is not subject to shocks. The electricity prices develop according to the historical price development (ElCom, 2020) and the appliance prices according to the historical consumer price index (BFS, 2020). As in SFOE (2018), the total stock of electrical appliances increases slightly over time, but household electricity consumption (median and average) decreases slightly as the proportion of energy-efficient appliances increases (left side in Figure 4).

As a first scenario, we simulate an increase in electricity prices. Up to period 4, electricity prices develop according to the historical price development. In period 4 the electricity price increases by 20% and will remain at this level in the following periods. Households react to this price increase by reducing their electricity consumption compared to the base case according to the price elasticity of approx. -0.6 (Boogen et al., 2014, right side of Figure 4). The effect is the same for all households, since we assume the same price elasticity for all households.

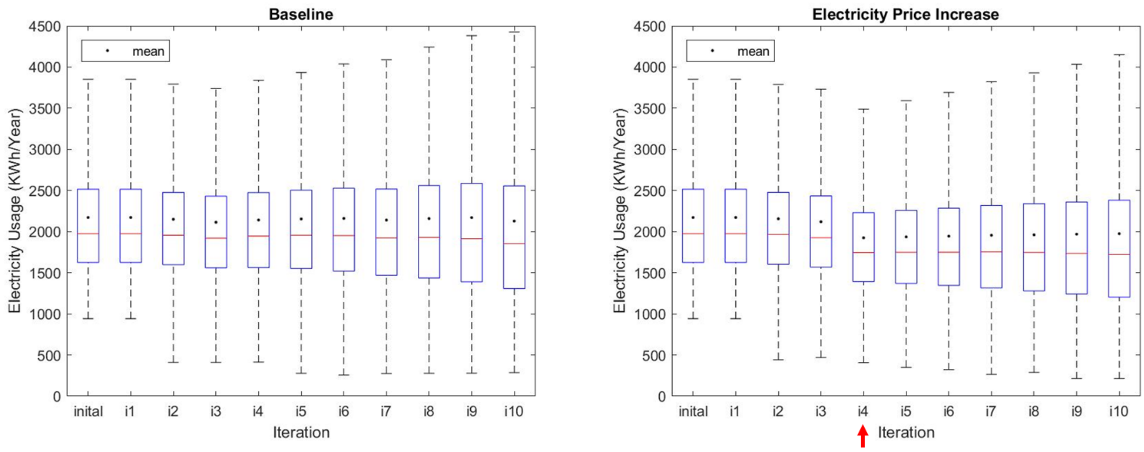

Figure 4. Electricity usage in the base case and electricity price shock scenarios.

Electricity: Norms campaign on effort

In a next scenario we will simulate a possible SFOE campaign that uses the channel of descriptive norms to increase the efforts of households to reduce their electricity usage. However, the exact magnitude of the campaign's impact on household efforts is only exemplary here. In our scenario, the campaign occurs once in period 4. In total across all households (right side of Figure 5), the campaign leads to an increase in household efforts in period 4 and a resulting decrease in electricity usage.

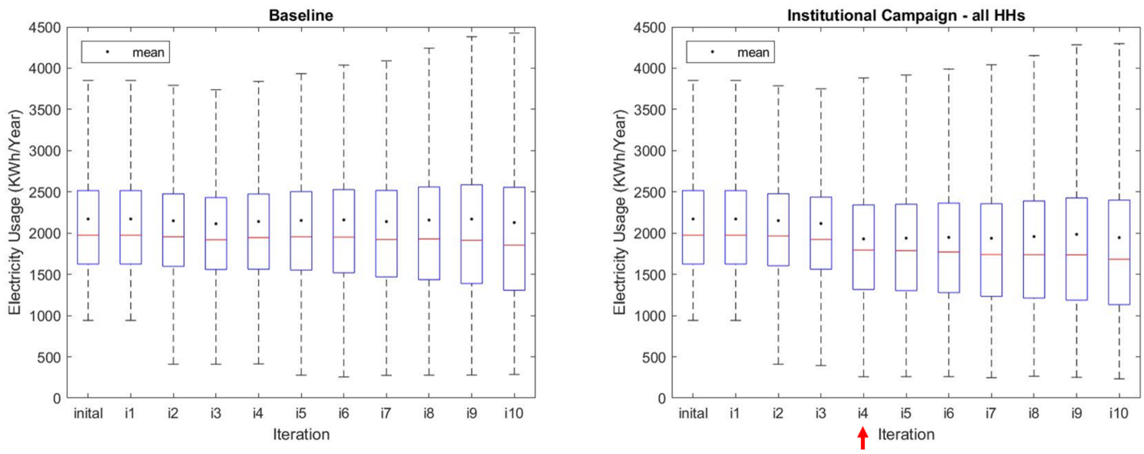

Figure 5. Electricity usage in the base case and institutional campaign scenarios.

A closer look at the results by dividing households into subgroups according to their level of trust and norms illustrates the impact of the institutional campaign in more detail. Households that do not take up information from the SFOE and/or have a low level of trust in the SFOE and a low descriptive norm level do not respond to the campaign (left side of Figure 6). Households that take up information from the SFOE and have a high level of trust in the SFOE and a high descriptive norms level respond to the campaign by increasing their efforts to reduce their electricity usage. Consequently, the electricity usage of these households has decreased in period 4 (right side of Figure 6). After period 4, the effort of these households has again decreased slightly, which leads to a slight increase in electricity usage over time. As these households interact with other households in the conversations, their effort is influenced by the interaction with these other households. As households with high effort and norms can also have conversations with other households with low effort and norms, their effort might be reduced again.

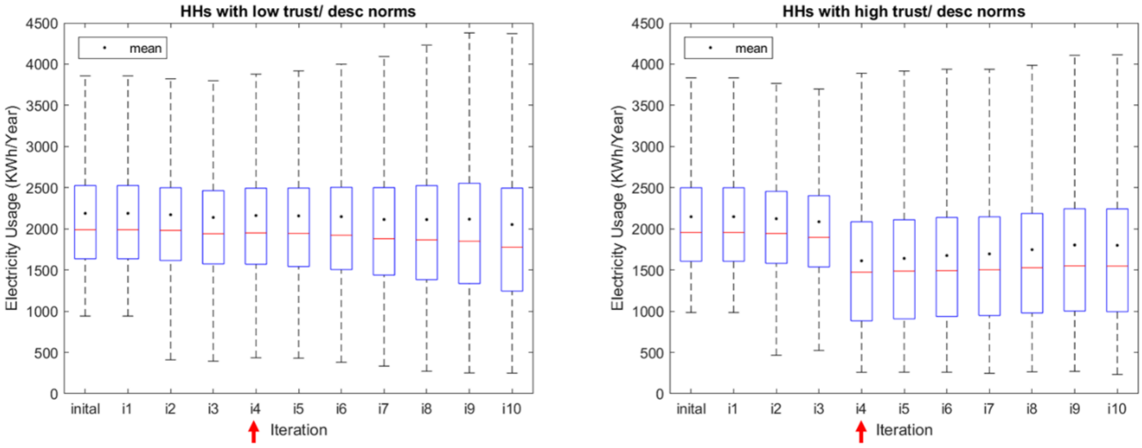

Figure 6. Electricity usage by subgroup in the base case and institutional campaign scenarios.

Heating: Persistent electricity price shock

In the case of heating ABM, changes in the accommodation situation or with regard to the heating system have a different dimension than changes to electrical appliances, as these are less frequent. For this reason, the base case does not lead to major changes in the accommodation situation of households or changes in the heating system. In the 10 periods considered here, households change their accommodation situation or heating system only marginally. Consequently, the heat energy usage in the base case is relatively stable (left side of Figure 7).

In the fuel price scenario, the heat price for households increases by 50% in period 4 due to an increase in fuel prices. After period 4 the prices remain on this level. As shown in Figure 7 (right side), households react to this price increase by reducing their heat energy usage in period 4. Compared to the electricity model, however, the price response in the heat model is much less pronounced, since we currently assume a lower price elasticity for heating than for electricity (approx. -0.2 for heating based on Bach et al., 2019).

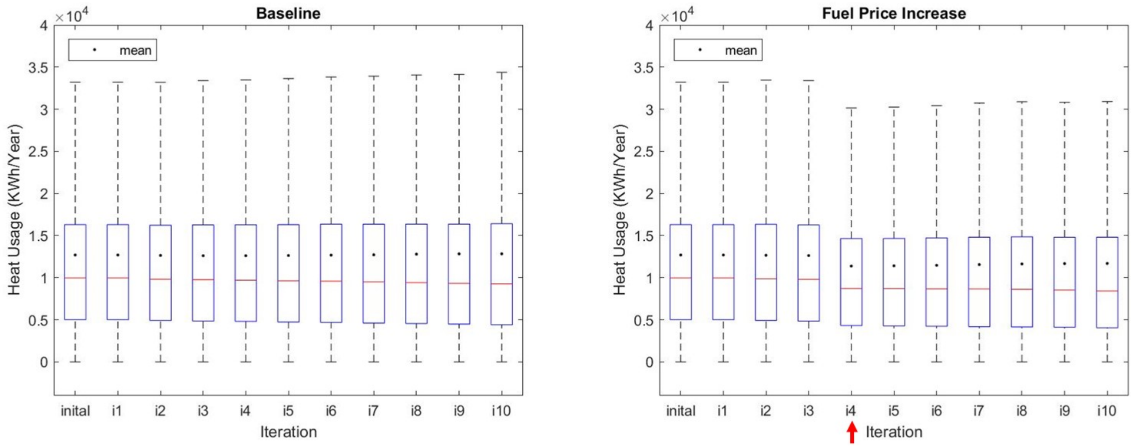

Figure 7. Heat energy usage in the base case and electricity price shock scenarios.

Heating: Norms campaign on effort

Next, we will again simulate a possible SFOE campaign that uses the channel of descriptive norms to increase the efforts of households to reduce their heat energy usage. As in the electricity model, the campaign leads in aggregate to an increase in household efforts and thus to a decrease in heating energy usage compared to the base case (right side of Figure 8).

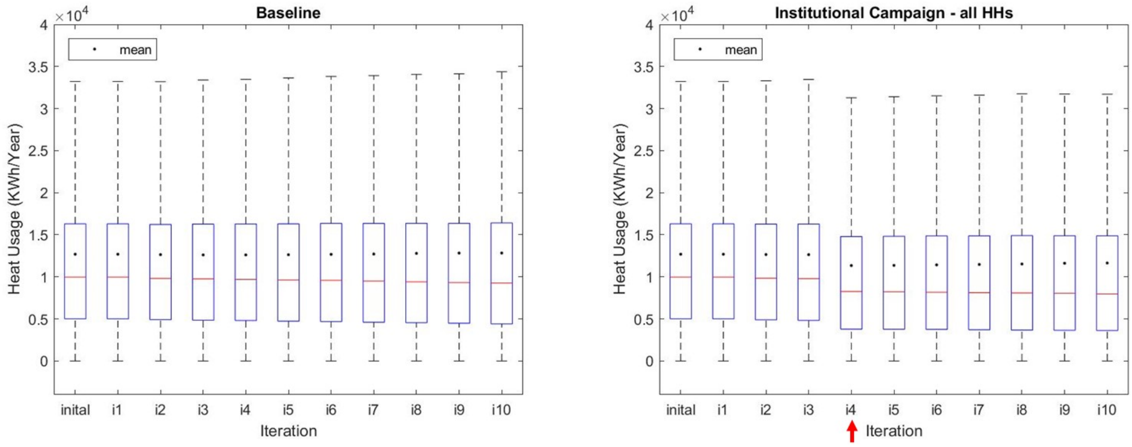

Figure 8. Heat energy usage in the base case and institutional campaign scenarios.

A closer look at the results by dividing households into subgroups according to their level of trust and norms once again illustrates the impact of the institutional campaign in more detail. As in the electricity model, only households with a high level of trust in the SFOE and a high descriptive norms level respond to the campaign by increasing their efforts and consequently reducing their heat energy usage (right side of Figure 9). Households with low trust and low descriptive norms do not respond to the campaign (left side of Figure 9).

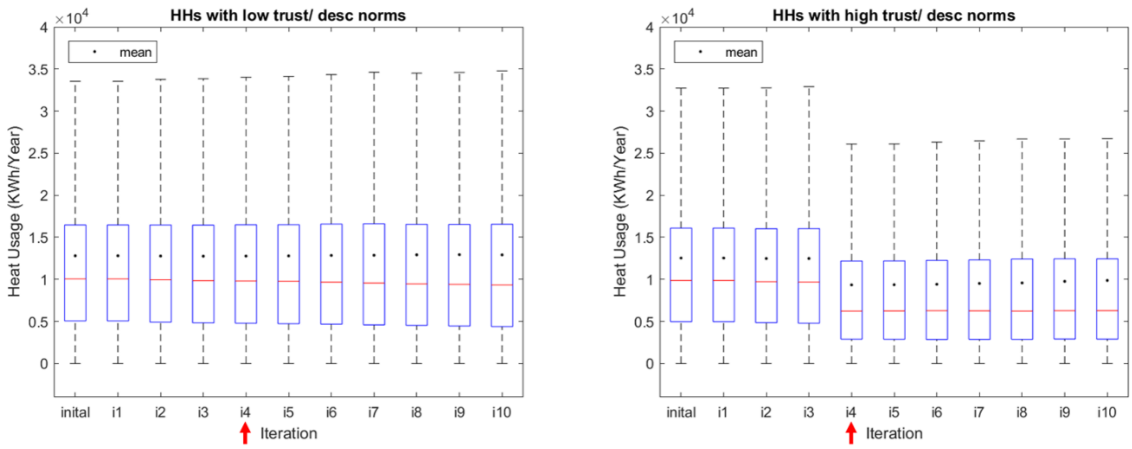

Figure 9. Heat energy usage by subgroup in the base case and institutional campaign scenarios.

4 Evaluation of results to date

4.1 Workstream 1 “Empirical Analysis”

Regarding the SHEDS assessment, the analysis provides experimental evidence for the effectiveness of soft incentives for home relocation decisions. The tested measures have an impact on the choice of housing regarding energy-conserving characteristics. This influence is especially relevant because it can aid in the downsizing of living space, which can contribute to a reduction of heat-related energy consumption of households.

Regarding the municipality assessment, the data collection and the first draft of the econometric analysis regarding mobility decisions are finished. We have started collecting information regarding electricity consumption at the municipal level. We have sent questionnaires to all the Swiss utilities (excluding the Italian region) that serve a single municipality. However, at the moment, the data that we have collected is not enough to conduct an econometric analysis and consequently, we are not yet able to make a final evaluation.

4.2 Workstream 2 “Agent-based modelling”

Overall, the exemplary scenarios presented in Section 3.2 showcase that the agent based model formulation can help to understand different transition channels of energy policies and campaigns. The household characteristics can likely provide a lever for tailoring interventions. Albeit the results are not yet calibrated in detail they allow us to identify relevant scenario structures for the final assessment in 2021.

5 Next steps

Following the adjusted time plan of the project, the empirical assessment will be finalized in early 2021 while the model assessment will continue until summer 2021. A final report is scheduled to be provided in fall of 2021.

Comparing the progress in 2020 with the projected timeline, the intended start of the model-based scenario simulations had to be postponed (Tasks 2.2 for electricity and heating). As explained above the last SHEDS wave was delayed due to Covid-19. Similar the investigation of suitable electricity data on the municipality level took longer, and unfortunately did not provide a usable dataset yet. As both, the SHEDS data and the municipality date are used to calibrate the ABM, we decided to delay the actual calibration and scenario simulations to be able to include the latest datasets. With the model framework finalized and the scenario outlet to be discussed on the joint project workshop with the SFOE in November 2020, the actual model calibration and scenario runs are rescheduled to early 2021. We expect to finish these project steps for all models (electricity, heating, mobility) until the second Quarter of 2021.

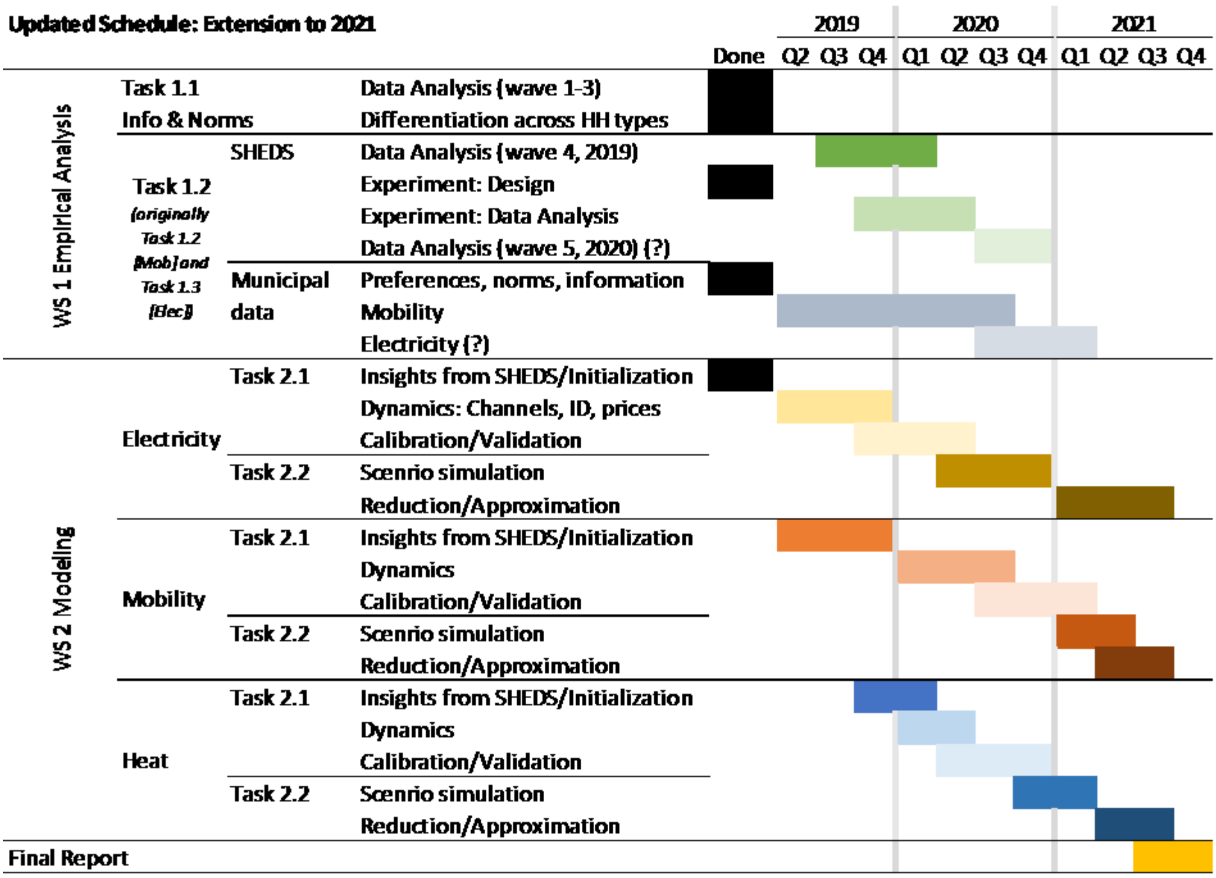

Figure 10: Project timeline (updated for the extension until 2021).

5.1 Workstream 1 "Empirical Analysis

Regarding the SHEDS assessment, the obtained results of the choice experiment are currently summarized and prepared for a journal publication. As a last SHEDS-based activity in Workstream 1, we will evaluate the fifth wave of SHEDS. This task had to be pushed back this year because the survey was run with a delay due to the Covid-19 pandemic.

Regarding the municipal data, we will improve the results for the mobility decisions in the first draft of the econometric estimation. We will continue gathering data on electricity consumption and exploring alternative data sources until the end of 2020. If we get the appropriate data, we will apply the same econometric approach as for the mobility decisions.

5.2 Workstream 2 “Agent-based modelling”

As explained above, the different scenarios and sensitivity cases will be simulated and the results will be evaluated following a final discussion on scenario design with the SFOE in November 2020. We plan to finish the model calibration until February 2021 and finalize the scenario runs until April. Building upon the insights obtained with the ABM approach the last step of WS2 will be initialized in spring 2021: the approximation of the obtained results for classical bottom up energy models.

6 National and international cooperation

The discrete choice experiment that was implemented in the 2019 wave of SHEDS was designed in cooperation with researchers from the Sustainability Research Group of the University of Basel and from the Institute of Sustainable Development of the Zurich University of Applied Sciences. Furthermore, we obtained price information for the experiment from Fahrländer Partner AG, a space development consultancy from Zurich.

7 Publications

There were no project-related publications in 2020.

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