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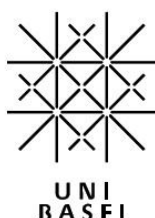
Department of the Environment,
Transport, Energy and Communication DETEC

Swiss Federal Office of Energy SFOE
Energy Research

Intermediate/Annual report from 30.11.2018

Reducing Swiss household energy demand

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



In cooperation with the CTI

 **Energy funding programme**
Swiss Competence Centers for Energy Research

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Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Swiss Confederation

Commission for Technology and Innovation CTI

Date: 30 November 2018

Place: Bern

Publisher:

Swiss Federal Office of Energy SFOE
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SFOE contract number: SH/8100087-00-01-02

The author of this report bears the entire responsibility for the content and for the conclusions drawn therefrom.



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. In 2018, we have completed the general analysis of the survey data, commenced the detailed analysis for mobility data, and developed a prototype of the agent-based model. Results so far show that social norms and information influence individual energy-related behavior, both with regard to investments and with regard to usage. However, 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.

Zusammenfassung

In diesem Projekt untersuchen wir welchen Einfluss soziale Normen und Information 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. 2018 haben wir die allgemeine Analyse der Befragungsdaten abgeschlossen und eine spezifische Analyse für den Bereich Mobilität begonnen. Zudem haben wir einen Prototypen des agenten-basierten Modells entwickelt. Unsere bisherigen Ergebnisse zeigen, dass soziale Normen und Information individuelles Verhalten im Energiebereich beeinflussen, sowohl in Bezug auf Investitions- als auch auf Nutzungsverhalten. Allerdings bestehen erhebliche Unterschiede im Einfluss sozialer Normen und Information 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.





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List of abbreviations

ABM	Agent-based model
EEA	Energy-efficient appliances
EU	Electricity usage
LEA	Labeled electric appliances
SHEDS	Swiss Household Energy Demand Survey



1 Context

1.1 Background / Motivation

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 and 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 first 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 (formation of social norms, diffusion of information). A reasonable 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 Goals

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 a) interactions with monetary incentives (for electricity and, if feasible, for mobility), b) different types of households (population segments) and c) their interactions. This model-based assessment rests upon a detailed empirical assessment of the effects of social norms, information, and monetary incentives (electricity and possibly mobility) on the *individual level*.

On the individual level, we use survey data to analyze the relation between energy literacy, the responsiveness to social norms, monetary incentives 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 cross-checked 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 policies 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 Organization of the project: Workstream and tasks

The project consists of two parallel streams. Workstream 1 “Empirical Analysis” analyzes 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 in different household types and of the interactions stemming from information diffusion and the formation of social norms.

The empirical analysis consists of three steps. In Task 1.1 “Information and Social Norms”, survey data is used to analyze the influence of social norms, information, and monetary incentives on individual energy use (electricity, heating (without monetary incentives), mobility) for different clusters of households (population segments). Task 1.2 combines additional survey data and municipal data for a more detailed analysis of energy-relevant mobility behavior. Task 1.3 does the same for electricity use.

The model-based analysis in workstream 2 consists of two tasks. In Task 2.1 “Design and Calibration”, an agent-based model (ABM) of Swiss household energy demand is developed that describes the behavior of consumer agents that are influenced by social norms, information and policy interventions. The model describes feedback effects arising from changing social norms and information diffusion and differentiates between different household clusters (population segments). It thus can provide information on aggregate effects of policy interventions and on the effects of interventions tailored to specific household types. In Task 2.2 “Application and Approximation”, the model will be applied to assess a range of interventions and an approximate model will be derived that is sufficiently simple for being used in general equilibrium models.

2 Approach and methodology

2.1 Workstream 1 “Empirical Analysis”

For Task 1.1. “Information and Social Norms” data from the Swiss Household Energy Demand Survey (SHEDS) has been analyzed. The SHEDS covers energy demand in the three areas electricity, heating (space and water) and mobility. So far, three survey waves for the years 2016, 2017 and 2018 are available. As the survey is a rolling household panel representative for the German and French speaking regions of Switzerland with new respondents being added each year, we have pooled the data across time and have conducted a cross-sectional analysis using year fixed effects. We have used various types of regression models to analyze different household energy consumption behavior with regard to social norms and energy literacy. In the regression models, we have included control variables such as socio-economic, accommodation-specific and energy-demand-related variables.

To analyze heterogeneity between different types of households, we have grouped households into five clusters. After trying several clustering algorithms, we have settled on a manual clustering approach that



fits best to our purpose.¹ Here, we have divided households along the two dimensions age and place of living. The assignment of household clusters to combinations of these two variables is described in Table 1.

		Place of living	
		City	Agglomeration & Countryside
Age	20 - 39	Cluster 1	Cluster 2
	40 - 64	Cluster 3	Cluster 4
	65 +	Cluster 5	

Table 1: Household clustering

Our explanatory variables of interest are energy literacy and social norms. In SHEDS, energy literacy is an index ranging from 0 to 11 that is constructed from multiple questions, which test respondents' energy-related knowledge. The design of this index draws on previous work by Blasch et al. (2017).

Regarding social norms, we have distinguished between two kinds of social norms: injunctive and descriptive norms. Injunctive norms describe what behavior is socially approved or disapproved (Cialdini et al., 1991). In our analysis, injunctive norms refer to a respondent's perceived expectations of her peers for her to behave in an environmentally friendly manner. Descriptive norms reflect perceived environmentally friendly behavior of peers. Responsiveness to both types of norms are measured on a Likert scale ranging from 1 to 5, where 1 indicates no perception and 5 indicates a strong perception of the respective norm. To prepare the corresponding modelling in Task 2.1, we have included a new question in SHEDS in 2018 that covers a national social norm as a complement to social norms transmitted via more local peer networks.

Regarding monetary incentives, we have started to use SHEDS data to assess the influence of prices on energy use for electricity use. However, results so far do not conform to prior expectations (see the results section) and require some further work based on the more detailed data becoming available in 2019 (SHEDS wave focusing on electricity, municipal data for Task 1.3). For mobility, the analysis of the more detailed data from the 2018 wave has commenced but not yet delivered sufficient results.

The work in Task 1.1 has been (almost) completed. Results are described in the following section. To get feedback on our approach and results, we have invited a group of experts from other disciplines (social psychology, sociology) to a workshop in April 2018. The workshop has helped us considerably in interpreting our results and in setting up the next steps of our analysis. It will be repeated in 2019.

For Task 1.2 "Mobility", work has commenced. Using the data from the 2018 wave of SHEDS, which focuses on mobility, we have started a more detailed analysis of the influence of social norms and information on individual mobility behavior. Also, we have started to gather municipal data as a second data source for this task. As we will not have access to detailed individual information here, proxies have to be constructed for social norms and information and fewer dependent variables will be available. However, this analysis will provide an important check of our results, as it relates to observed (not stated) behavior and is based on a completely independent data source.

As a proxy for energy literacy, we will construct an index related to media coverage (including both local and national newspapers) of topics that match with the items we used to construct energy literacy at the household level (energy label, costs of electricity, energy prices, energy conservation, etc.). If data

¹ The clustering is applied in both workstreams. For the validation step of our project, it also needs to be applied to municipal data. Hence, we chose the variables and their partition values accordingly.



should be available, we will also try to construct an alternative index of energy literacy that is based on observed competences (e.g., a switch to LED lighting).

Regarding social norms at the municipal level, we currently aim to consider four indicators as proxies for social norms. One indicator can be based on voting behavior during national, cantonal and local elections. A second indicator considers party *membership* in each municipality. As a third indicator, we intend to use municipal data on environmental ballots. This indicator is an alternative proxy of green ideology and is less influenced by elections events. The fourth indicator focuses on green business. A green business is a socially and environmentally responsible business that provides green products or services and that operates in ways that solve rather than cause social and environmental problems. Green people are more likely to move to a municipality with a higher rate of green business. Alternatively, we could try to use data on the share of green products at stores of major retailers (Coop, and Migros).

The proxies for information and social norms will be used in Tasks 1.2 and 1.3. As dependent variables, we will use car registration data (number of cars, energy efficiency) for Task 1.2 and are currently trying to gain access to data on average household electricity consumption on the municipal level for Task 1.3. In addition, we will use the municipal data as a second data source to have a closer look at the interaction of monetary and non-monetary incentives.

2.2 Workstream 2 “Agent-based modelling”

In this workstream, we develop an agent-based model (ABM) that is based on the results of the empirical analysis in Workstream 1 and thus reflects the details of the SHEDS data. For its implementation we follow three steps: 1) model development, 2) validation, and 3) policy evaluation. We are currently in Step 1 (model development). For Step 2, we will use the municipal data gathered for Tasks 1.2 and 1.3.

With regard to the model development, the SHEDS data allows us to model a set of agents that reflects the clustering of households of Task 1.1 and accounts for additional heterogeneity observed in the SHEDS data, such as household size (≤ 2 or > 2), the housing status (tenant or owner) and the income level ($< 9'000$ CHF/month or $\geq 9'000$ CHF/month). We thus consider a total of 40 different types of households in the model.

The model also accounts for differentiated effects of norms and information for different types of energy use and the five main clusters of households. To transfer the relevant information from the empirical analysis, we have implemented a scalable and flexible method to extract the relevant descriptive statistics, so that the model can be easily updated whenever new empirical information is gained. When assigning the initial values for households, we draw for each household from the estimated distribution of the variable at hand, which is specific for any given combination of cluster and category.

From the three areas of household energy use (electricity, mobility and heat), we have started with electricity. This comprises investment in electrical appliances and electricity usage. With regard to the investment-side, we have considered the total number of electric appliances and the number of energy efficient appliances (according to the efficiency label). With regard to the electricity usage, we have focused on electricity usage in kWh. Figure 1 provides an example for the cluster-specific assignment of the initial electricity use.

To model interactions between agents in our model, we have implemented a flexible network approach. Using this approach, we are able to set up multiple network structures that exist at the same time. Each network structure differs by three characteristics: the (average) size of the resulting networks, the share of households that belong to more than one network of the network structure, and how correlated each network is over clusters. To illustrate, we can assign households to a family, friends and neighborhood network structure, such that each household belongs to at least one of each. Some households might



belong to more than one network of friends and some might have “no” family, which would imply that they are the single member in their family network. Appendix 1 contains examples of three possible network structures existing at the same time. These network structures will be used to track the influence a household has on its network members via social norms or via the provision and diffusion of information.

Our flexible setup to create network structures also allows us to model peer effects. For this, we can create smaller as well as larger networks of households that pursue a similar lifestyle. We will use the former to model local peer effects and the large-scale peer networks to model regional or national peer effects. The differences in responsiveness to local and national social norms has been assessed in Task 1.1.

As SHEDS does not allow to draw conclusions on the specification of the network structures that link households and little information is available from other sources, we will define and work with different network structures to estimate the robustness of our results. So far, we have limited our analysis to the effects of social norms. Information diffusion will be introduced to the model in 2019.

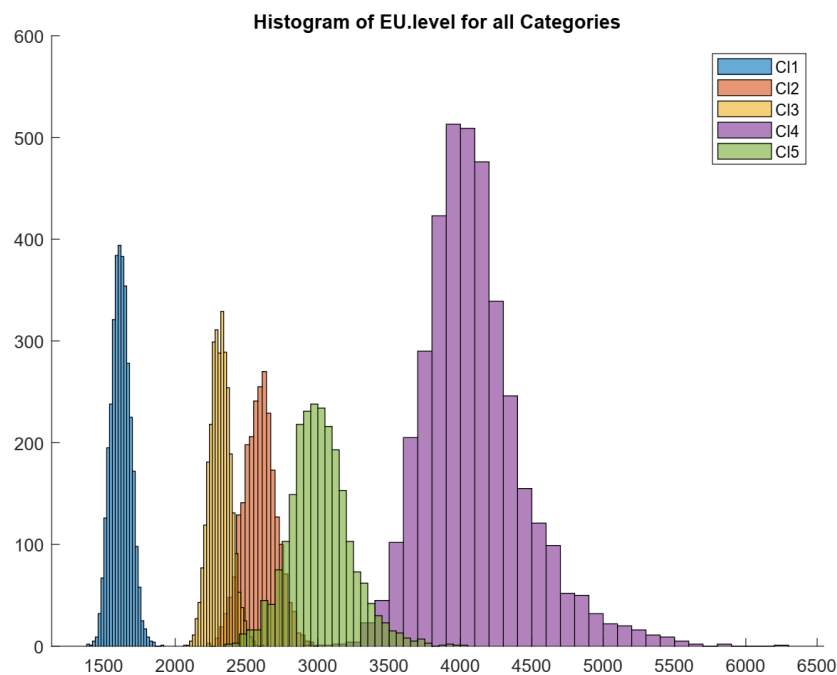


Figure 1: Distribution of initial electricity consumption levels (in kWh/a) by cluster.

3 Results

3.1 Workstream 1 “Empirical Analysis”

The analysis of SHEDS data in Task 1.1 using the previously mentioned methods (see 2.1) has resulted in the findings summarized in Table 2, which displays statistically significant relations between soft incentives and various behavioral variables.



	<i>Investment Choices</i>			<i>Usage Choices</i>		
	<i>SHEDS Data</i>	<i>Soft Incentives</i>		<i>SHEDS Data</i>	<i>Soft Incentives</i>	
		<i>Literacy</i>	<i>Social Norms</i>		<i>Literacy</i>	<i>Social Norms</i>
Mobility	Public transport subscription	x	x	Preferred mode of transport: work		x
				Preferred mode of transport: leisure	x	x
	Type of car (engine)	x		Reported average distance driven by car	x	x
	Ownership and number of cars/(motor-/e-)bikes	x	x	Number of flights	x	<i>x (positive correlation)</i>
Heat	Type of system for heating			Costs of heating based on actual consumption	<i>x (positive correlation)</i>	
				Average room temperature	x	x
				Index for energy-saving heating behavior	x	x
	Type of system for warm water	x		Venting behavior	x	
				Frequency of warm baths/showers		
				Turning off shower while applying products	x	x
Electricity	Number of appliances	x	x	Usage frequency and duration of usage	x	x (duration)
	Energy efficiency label of appliances	<i>x (negative correlation)</i>	x (TV, fridge)	Amount of electricity consumed and costs	<i>x (positive correlation, concave)</i>	x (costs)
	Tariff choice	x	x	Devices switch-off behavior		x

Table 2: Significant correlations between soft incentives and energy-related choices for the full sample (marked with an x).

Comparing the results for all three areas of energy demand, our analysis suggests soft incentives to be particularly relevant for mobility behavior. We find statistically significant relations to lower energy-consuming behavior across investment as well as usage choices for both types of soft incentives. However,



there also exist some differences. We only find energy literacy to be positively related to the investment in electric cars, whereas we cannot find such evidence for social norms. Also, while both soft incentives are positively correlated with the choice of public transport over car for leisure activities, this is only the case for social norms when analyzing commuting behavior.

For space heating and warm water, we have found only limited evidence for effects of soft incentives in investment choices. Our analysis provides some indication of a positive relation between energy literacy and the probability of households investing in solar power for water heating. Households with a very high level of energy literacy have a higher predicted probability of having a solar-based system for warm water compared to households with a very low level of energy literacy (by six percentage points). Regarding energy usage, soft incentives are significantly correlated with energy-saving heating behavior, such as having a lower average room temperature. However, we do not find this relation represented in lower heating costs (based on actual consumption) for households with high levels of energy literacy or a strong responsiveness to social norms.

In the area of electricity, our analysis suggests that social norms are more relevant than energy literacy. Although both soft incentives are significantly correlated with more environmentally-friendly investment choices, we find more significant correlations with usage choices for social norms. Households who have a stronger perception of social norms regarding environmentally-friendly behavior tend to use electric appliances for a shorter period of time per day and save energy by switching them off completely instead of leaving them on standby. For the full sample, we then find an, on average, 15 percent lower electricity bill for households with a strong responsiveness to social norms compared to households who do not respond to social norms.

Social norms and literacy also differ with regard to the magnitude of their influence on behavior. As an example, Figure 2 depicts the predicted probabilities of car ownership in relation to social norms (injunctive norms) and energy literacy across different household clusters. As shown in Table 2, both influences are significant. However, Figure 2 shows that the magnitude of influence differs starkly.

It also highlights the relevance of the different household types. Households in Cluster 1 (young people living in urban areas) have a lower predicted probability of owning a car when they have a high level of literacy and a strong perception of social norms compared to households in the same cluster who do not have such strong values. In the case of energy literacy, the predicted probability is over 25 percentage points lower on average compared to 13 percentage points in relation to social norms.

In this example, Cluster 1 is the only household group with a significant relation for both types of soft incentives. For young people living in rural areas (Cluster 2) and for people in the middle age group living in urban areas (Cluster 3), there is evidence for a link between car ownership and energy literacy but not for an influence of social norms. Conversely, social norms is the only soft incentive in the middle age household group living in rural areas (Cluster 4) and in the senior household group (Cluster 5) for which we observe significantly lower probabilities of car ownership when the perception of social norms is strong.

Such differences across households are observable for investment and usage choices and for all three areas of energy demand. However, at this point, we can only report that there are substantial and important differences for the correlation of soft incentives and behavioral variables between different types of households. We are still working on aggregating the numerous results into an overall picture.

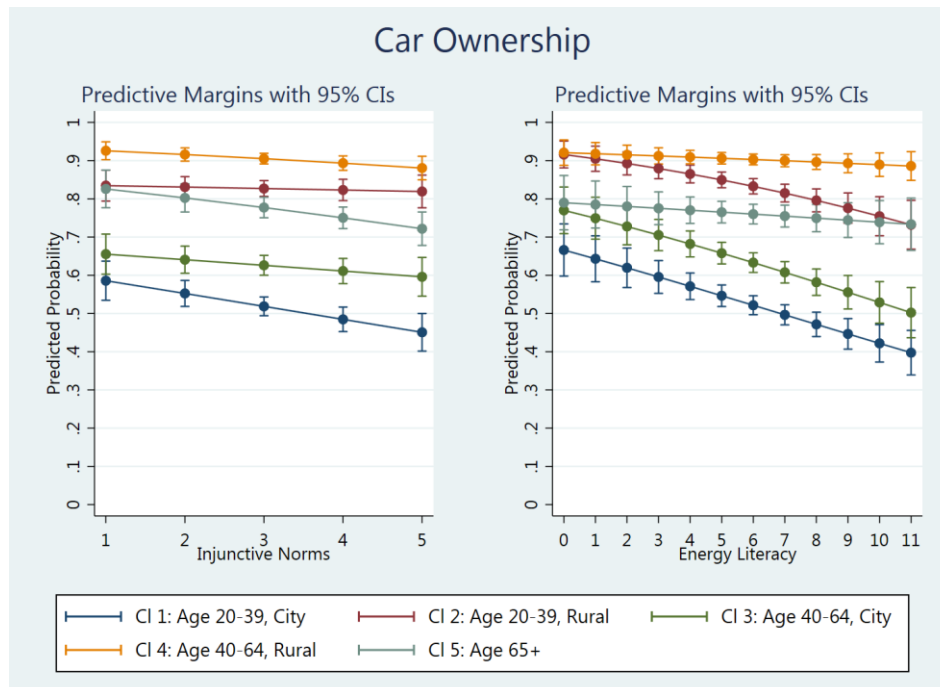


Figure 2: Predicted probabilities of owning a car in relation to injunctive norms and energy literacy across household clusters

Looking more closely at social norms, our analysis suggests that injunctive norms have a stronger influence on household energy demand than descriptive norms. Finally, for some behavioral variables, our analysis indicates significant relations with soft incentives for certain household clusters but not for the full sample. For example, although we do not find statistically significant correlations between soft incentives and electricity usage, we do find some evidence for such a correlation at the cluster level: Households in Cluster 5 with a strong perception of social norms have (on average) a 30 percent lower electricity usage than households without such a perception.

To analyze monetary incentives in the area of electricity, we have started to study the effect of electricity prices on household electricity consumption. However, the results do not conform to expectations and require further investigation. So far, they show rather limited evidence for an effect of the electricity price on electricity consumption. Whether households are price sensitive in this domain depends on the electricity mix product that they have chosen. For the full sample, we only observe a negative effect of the electricity price on the consumption for households who have chosen an electricity mix that is more expensive and has a high share of renewable energy. This is also true on the cluster level for most clusters. Only for Cluster 2, we have found a significant effect for households with the default electricity mix.

Given these results, we have abstained so far from estimating price elasticities for electricity and from analyzing the interactions between non-monetary and monetary incentives in this domain. We will do so, once we have checked the robustness of these results either with a second data source in Task 1.3 or with the SHEDS data from the next wave in 2019, which will focus on electricity.

Similarly, we have started to analyze price effects on mobility behavior, using data on fuel costs and taxes from SHEDS. However, as the most detailed data on mobility behavior became available only in May 2018, we have not yet gathered sufficient results to provide a comprehensive picture.



3.2 Workstream 2 “Agent-based modelling”

As reported above, for developing the agent-based model, we have focused, so far, on electricity usage and social norms. Using the SHEDS data and the results of the empirical analysis, we have set up the main structure of the model. Using assumptions on the replacement frequencies of electric appliances and on fluctuations of the electricity usage, we have added some dynamic elements to the model. For our first model runs, we have assumed that the observed starting point (i.e., the initialization calibration) resembles an “equilibrium” in the sense that we assume that the model fluctuates around its starting point. This has produced a “plain model” version, for which the evolution of investment- and usage-related measures can be observed in Figure 3. By construction, this model replicates the observations from SHEDS.

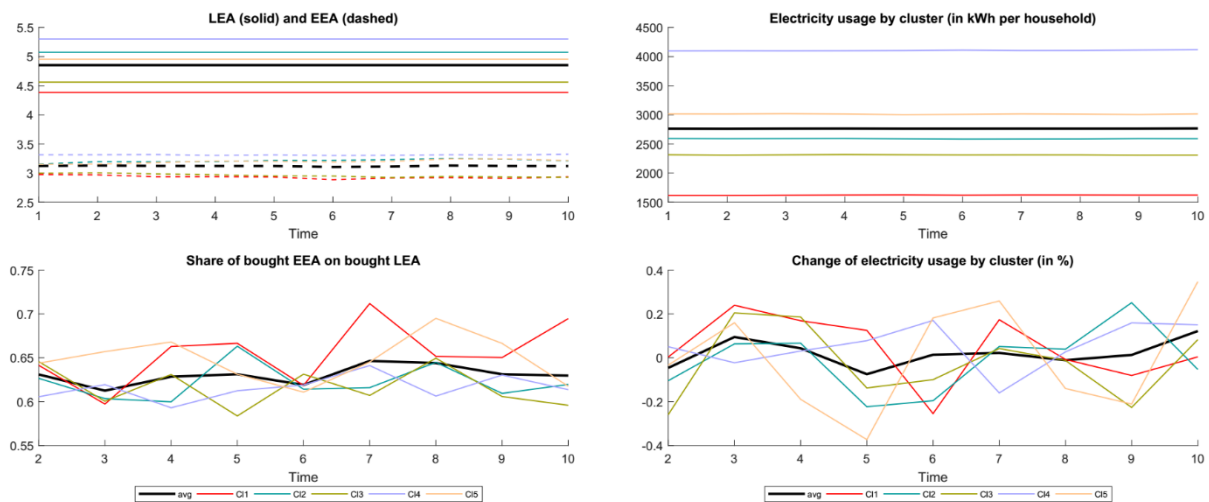


Figure 3: Model outcomes for plain model. Left plots show change of investment measures for electric appliances over time, right plots show usage measures. Both are fluctuating around its initialization values.

To analyze the influence of social norms and information in this model, we work on different options. One option is to interpret significant correlations of the empirical analysis as causal relationships. Then, whenever we “shock” the levels of explaining variables, the levels of the dependent variables adjust.

A second option is to use a range of heuristics. For example, we can implement a network effect in which we let every household mimic (to a certain extent) the most energy-efficient household in his family-network when buying a new electric appliance. Figure 4 illustrates such an implementation. Compared to Figure 3, this network effect is added and this shows that over time the stock of energy efficient appliances converges to the actual stock (upper left plot), which is also reflected in the share of bought EEA on bought LEA in every period (lower left plot). With regard to electricity usage, the model in Figure 4 treats the significantly negative correlation of descriptive norm levels and energy usage, which we have found for cluster 5 (old households) as a causal relation. In other words, we have operationalized a cluster-specific channel based on the correlation analysis. As cluster 5 initially has an above-average electricity consumption level (see “Time 1” in upper right plot), the households of this cluster decrease their electricity use over time at a decreasing rate (lower right plot).

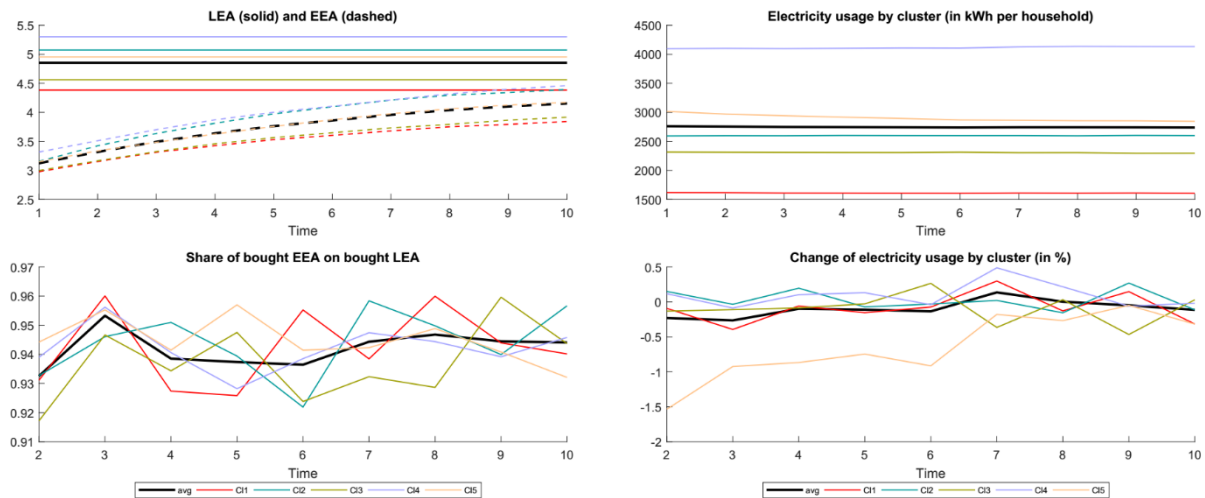


Figure 4: Model outcomes for the plain model with additional networks effects (on the investment side) and additional cluster-specific effects of descriptive norms on electricity usage.

In addition, we have allowed for systematically different trends for the change of the energy consumption of rich and poor households by including an investment-usage link whenever a household replaces a non-EEA with an EEA. Overall, we have now covered 11 channels that allow households to make investment and usage decisions related to the demand for electricity. In the “baseline version” of the model, which is shown in Figure 5, we have activated all of the potential channels.

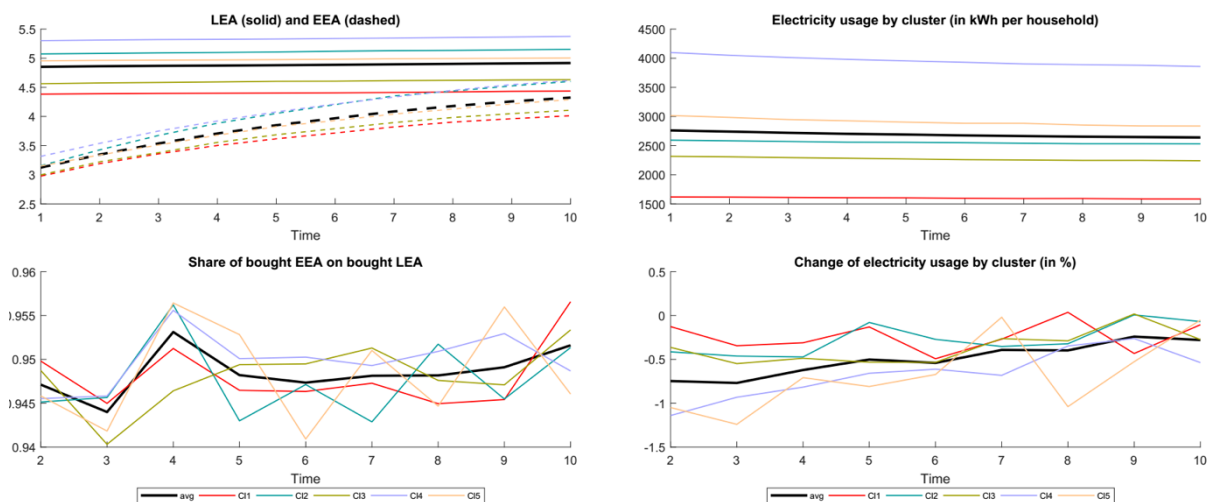


Figure 5: Model outcomes for the baseline model. In this version of the model we have allowed for all of the modelled effects and trends, activated with reasonable levels of activity.

4 Evaluation 2018 and outlook for 2019

In 2018, we have completed Task 1.1, commenced Task 1.2 (work with survey data almost completed, municipal data being collected) and developed a prototype of the agent-based model for electricity use in Task 2.1. The first workshop with experts described in the application has been conducted.

Compared to the project application, we are thus somewhat behind the schedule w.r.t. Task 1.2, which is mostly due to Dr. Lechthaler-Felber leaving the project in May 2018 and Dr. Dato starting in this



position in October 2018. However, we are convinced that the delay can be recovered, so that the project will be completed in 2020, as described in the application.

Given the delay in Task 1.2, we have decided to move the second workshop with the external experts to 2019, instead of conducting the workshop end of 2018. For this and the other workshops, Prof. Paul Burger, head of the sustainable research group at the University of Basel, has generously accepted to join the board of experts, providing additional expertise.

As preparation for the work in 2019, the collection of municipal data for Tasks 1.2, 1.3 and 2.1 has been started and new questions for the next wave of SHEDS are being prepared. In 2019, we will conclude the analysis of SHEDS with the fourth survey wave, which will have a focus on electricity (connecting to Task 1.3 as planned). This also allows us to have a closer look at the price sensitivity of households and the interaction between soft incentives and monetary incentives. For the next year, work in Workstream 1 will mostly focus on municipal data and the analysis of the fourth survey wave. Given the above-mentioned delay, we expect to finish Tasks 1.2 and 1.3 early in 2020.

In Workstream 2, we have successfully laid the basis for diving into the energy-related decision-making processes of households. We have built a prototype model for electricity use that includes social norms and have gained a thorough understanding of how to use empirical results for developing the agent-based model. We can use the insights gained in the field of electricity when setting up the model for mobility and heat. As next steps, we will set up the model for mobility behavior and then include information diffusion as well as local and national peer effects in our model (electricity and mobility). Finally, we will extend the model to heat. The model development will be completed in 2019, so that first scenarios will be analyzed mid-2019, as described in the project application.



5 Publications

Poster Presented at the 5th SCCER CREST Annual Conference: The Future of Energy (September 12, 2018 in Basel) and at the Energy Modelling Platform for Europe (EMP-E) 2018 – Modelling clean energy pathways (September 25-26, 2018 in Brussels).



6 References

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7 Appendix

7.1 Appendix 1: Examples of network structures

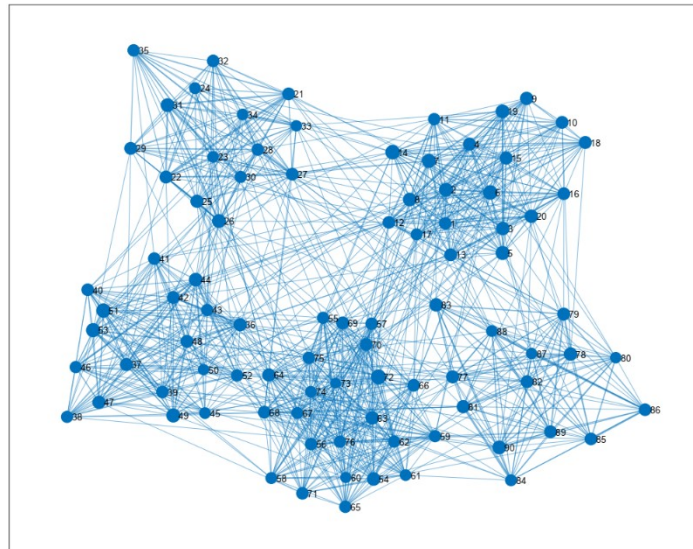


Figure A1: Graph for network Neighborhood ($N = 14954$, $\text{SetMeanSize} = 200$, $\text{ActMeanSize} = 200$, $\text{BelongTwo} = 0.20$, $\text{ClCorr} = 0.95$)

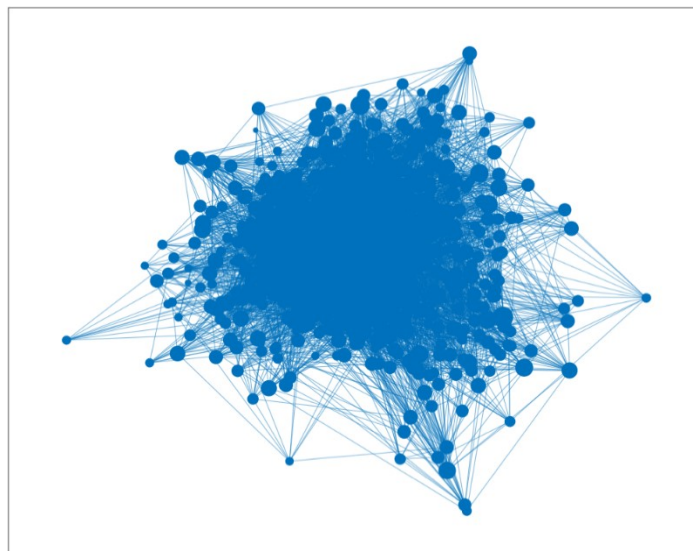


Figure A2: Graph for network Friends ($N = 14954$, $\text{SetMeanSize} = 25$, $\text{ActMeanSize} = 25$, $\text{BelongTwo} = 0.50$, $\text{ClCorr} = 0.60$)

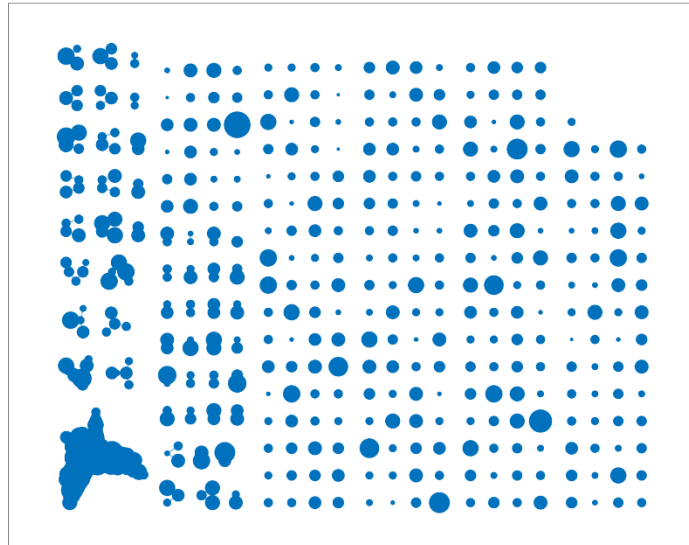


Figure A3: Graph for network Family ($N = 14954$, SetMeanSize = 10, ActMeanSize = 10, BelongTwo = 0.10, ClCorr = 0.30)