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Federal Department of the Environment, Transport, Energy and Communications DETEC

Swiss Federal Office of Energy SFOE
Energy Research and Cleantech Division

Final report dated 22.07.2022

Reducing Swiss household energy demand

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

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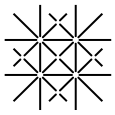

Date: 22 July 2022

Location: Bern

Publisher:
Swiss Federal Office of Energy SFOE
Energy Research and Cleantech
CH-3003 Bern
www.bfe.admin.ch

Co-financing: No

Subsidy recipients:
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SFOE contract number: SH/8100087-00-01-02

Zusammenfassung

In diesem Projekt haben wir die Wirkungen von Informationen, sozialen Normen (injunktive und deskriptive Normen) sowie Preisen auf die Energienachfragen von Haushalten in den Bereich Strom, Wärme (Raumwärme und Warmwasser) und Mobilität untersucht. Das Alleinstellungsmerkmal des Projekts ist die kombinierte Verwendung einer empirischen Analyse, die auf detaillierten Survey-Daten basiert, und einem modellbasierten Ansatz für die Aggregation individuellen Verhaltens und für die Simulation von Politikszenarien.

Für die empirische Analyse haben wir Daten aus der Befragung SHEDS (Swiss Household Energy Demand Survey) verwendet, welche Informationen über die Investitions- und Nutzungsentscheidungen von 5000 Schweizer Haushalten (repräsentativ für die deutsch- und französischsprachige Schweiz) über 5 Jahre in den drei genannten Bereichen liefert und zudem detaillierte Informationen zu sozio-demographischen Charakteristiken, Einstellungen und Werthaltungen, Energy Literacy, Empfänglichkeit für Peer-Pressure und soziale Normen, sowie Vertrauen in verschiedene Anbieter von energierelevanten Informationen beinhaltet. Mit diesen Daten haben wir den Einfluss von Informationen, injunktiven und deskriptiven Normen sowie Energiepreisen auf das Investitions- und Nutzungsverhalten der Haushalte ökonometrisch geschätzt. Zudem haben wir die Haushalte in 5 Cluster unterteilt (nach Alter und Wohnort, d.h. Stadt vs Land). Mittels einer erneuten Schätzung der statistischen Modelle haben wir untersucht, wie stark sich diese Cluster in Bezug auf ihre Reaktion auf 'weiche' Politikmassnahmen (Informationen, Normen) unterscheiden. Aufgrund der Kürze der Paneldaten (5 Jahre), sollten die empirischen Analysen mit Vorsicht interpretiert werden, da sie nur Korrelationen aber keine Kausalitäten aufzeigen können.

Die empirischen Analysen zeigen zum einen, dass Informationen und soziale Normen eine signifikante Korrelation mit energiebezogenem Haushaltsverhalten aufweisen, auch wenn der Zusammenhang stellenweise eher kleine Effekte vermuten lässt. Zum anderen zeigen die Analysen, dass sich die 5 Cluster erheblich in ihrer Antwort auf Informationen und soziale Normen unterscheiden; wir fanden stark abweichende Korrelationen für die verschiedenen Cluster. Schliesslich zeigt sich das Gleiche für die unterschiedlichen Energiebereiche, was zu recht komplexen Einflüssen weicher Instrumente auf den Energieverbrauch der Haushalte führt.

In einem zweiten Schritt haben wir diese Ergebnisse mit anderen Daten (BfS Daten auf Gemeindeebene) für den Bereich der Mobilität überprüft. Die Ergebnisse unterstützen die wesentlichen Schlussfolgerungen aus den ersten Analysen, insbesondere, dass es eine signifikante Korrelation zwischen weichen Instrumenten und energiebezogenem Verhalten gibt und dass sich diese Korrelation für verschiedene Haushaltstypen unterscheidet.

Schliesslich haben wir im Rahmen der empirischen Analyse ein Choice Experiment zum Thema Wohnortwahl durchgeführt (dieser Aspekt ist mit Survey-Daten nicht zugänglich aber für den Energieverbrauch bedeutsam). Auch diese Analyse unterstützt die Ergebnisse, dass weiche Instrumente Effekte auf den Haushaltsenergieverbrauch haben und diese sich zwischen Haushaltstypen unterscheiden.

In einem zweiten Projektteil haben wir die Ergebnisse und Daten der ersten empirischen Analyse verwendet, um ein agentenbasiertes Modell zu entwickeln, welches das Investitions- und Nutzungsverhalten der Haushalte in den drei Energiebereichen abbildet. Dabei wurden die Cluster der empirischen Analyse verwendet. Dieses Modell nutzt die empirisch bestimmten Einflüsse von Informationen, sozialen Normen und Preisen, sowie weitere Beziehungen (z.B. Vertrauen oder Empfänglichkeit für Peer-Pressure). Das Modell wird mit den SHEDS Daten initialisiert (z.B. bzgl. des Bestands an elektrischen Geräten, Fahrzeughaltung, Einkommen, Haushaltsgrösse). Interaktionen zwischen den Haushalten bildet das Modell durch Konversationen ab, welche Informationen oder Normen in Netzwerken transportieren (Familie, Freunde, Nachbarschaft) und damit eine Möglichkeit bieten, den Effekt von informations- oder normbasierten Kampagnen zu simulieren. Die Struktur der Konversationen wurde für den Bereich Mobilität mittels kantonaler Daten kalibriert.

Mit diesem Modell haben wir verschiedene Szenarien untersucht, zum Beispiel die Einführung einer CO2-Abgabe von 200 CHF/t, Subventionen für effiziente Geräte oder Elektrofahrzeuge, sowie informations- und normbasierten Kampagnen. Die Ergebnisse der Simulationen deuten darauf hin, dass Informationen alleine nur einen begrenzten Effekt auf die Energienutzung in allen drei Bereichen haben, dass normbasierte Kampagnen und monetäre Anreize aber deutlichen Einfluss besitzen können. Zudem zeigen die Ergebnisse, dass sich die Haushalte stark bezüglich ihrer Reaktion auf weiche Instrumente unterschieden, so dass bei Kampagnen ein gezieltes Adressieren einzelner Haushaltsgruppen sinnvoll sein könnte. Schliesslich deuten die Szenarienrechnungen darauf hin, dass die Kombination von monetären Anreizen und weichen Instrumenten zwar mehr Effekt hat als ein Instrument alleine, die kombinierte Wirkung aber sub-additiv ist, das heisst, der kombinierte Effekt ist kleiner als die Summe der Einzeleffekte. Dies bedeutet, dass eine Kombination von Instrumenten nützlich sein kann, ein gewisses Crowding-out aber zu erwarten ist.

Insgesamt lässt das Projekt Schlussfolgerungen sowohl für die zukünftige Forschung als auch für die Praxis zu. Für die Forschung legt es nahe, dass die Berücksichtigung von (etwas) Heterogenität bei den Haushalten in energie-ökonomischen Modellen sinnvoll sein dürfte. Diese Heterogenität sollte aber nicht reine Einkommensheterogenität sein, sondern eher unterschiedliche Lebenssituationen (Stadt vs Land, jung vs pensioniert) abbilden. Zudem zeigen unsere Ergebnisse, dass eine stärkere Berücksichtigung von weichen Instrumenten in energieökonomischen Simulationsmodellen angezeigt sein könnte; diese Instrumente zeigen keine sehr starke Wirkung, aber sie haben eine Wirkung und werden weniger kontrovers diskutiert (und sind daher möglicherweise einfacher einführbar).

In Bezug auf die Praxis legen unsere Ergebnisse nahe, dass ein gezielter Einsatz weicher Instrumente sinnvoll sein könnte. Unsere empirischen (und simulationsbasierten) Ergebnisse deuten darauf hin, dass weiche Instrumente nur bei einigen Haushaltsgruppen wirksam sind. Diese Gruppen sind leicht identifizierbar und adressierbar. Dementsprechend könnte es nützlich sein, genauer zu analysieren wie weiche Instrumente gestaltet werden können, um gezielt einzelne Haushaltsgruppen anzusprechen.

Résumé

Dans ce projet, nous avons analysé les effets de l'information, des normes sociales (injonctives et descriptives) et des prix sur la demande énergétique des ménages dans les domaines de l'électricité, du chauffage (espace et eau) et de la mobilité. La contribution unique du projet est l'utilisation jointe d'une analyse empirique basée sur des données d'enquête détaillées et une approche basée modèle pour l'agrégation et la simulation.

Pour l'analyse empirique, nous utilisons les données du SHEDS (Swiss Household Energy Demand Survey), qui contient des informations sur le comportement d'investissement et d'utilisation de 5'000 ménages suisses (représentatifs des régions suisses alémanique et romande) pendant 5 années dans les trois domaines d'utilisation de l'énergie ainsi que des informations détaillées sur les principales caractéristiques de ces ménages (par exemple, les données sociodémographiques, attitudes et valeurs, connaissances relatives à l'énergie, sensibilité à la pression des pairs et aux normes sociales, confiance dans différents fournisseurs d'informations liées à l'énergie). Sur la base de ces données, nous avons estimé l'influence de l'information, des normes injonctives et descriptives et des prix sur le comportement d'investissement et d'utilisation des ménages suisses dans les domaines de l'électricité, le chauffage et la mobilité. De plus, nous avons regroupé les ménages en 5 segments selon l'âge et le lieu de résidence (rural vs urbain). Pour voir si ces segments de ménages diffèrent en ce qui concerne leur réponse aux mesures politiques souples, nous avons réestimé nos modèles pour ces sous-échantillons. Du fait que l'analyse empirique est basée sur seulement 5 années d'observation (pour les données SHEDS), elle doit être interprétée avec précaution, c'est-à-dire comme montrant des corrélations et non des effets « causaux ».

Cette analyse empirique a d'abord montré que l'information et les normes sociales ont des corrélations significatives avec le comportement des ménages en matière d'énergie, bien que les impacts puissent être relativement faibles. Deuxièmement, cette analyse empirique a montré que les différents segments de ménages diffèrent considérablement dans leur réponse comportementale face à l'information et aux normes sociales, c'est-à-dire que nous avons trouvé des corrélations très différentes entre le comportement relatif à l'énergie et les instruments souples pour différents segments de ménages. De plus, il en va de même pour les trois domaines d'utilisation de l'énergie ainsi qu'entre les comportements d'investissement et d'utilisation, ce qui donne une image globale assez complexe de l'influence des instruments souples sur la consommation d'énergie des ménages.

Dans un second temps, nous avons vérifié ces résultats avec une source de données indépendante (données FOS pour les communes suisses) dans le domaine de la mobilité. Cette analyse soutient les principales conclusions de la première étape, en particulier que les instruments souples montrent une corrélation significative avec le comportement lié à l'énergie et que cette corrélation diffère selon les différents segments de ménages.

Dans la dernière partie de notre analyse empirique, nous avons mené une expérimentation des choix sur la relocalisation du domicile (un cadre de grande importance pour la consommation d'énergie qui ne peut pas être facilement analysé avec des données d'enquête) qui appuie à nouveau les résultats des autres évaluations empiriques que les instruments souples ont un effet et que cet effet diffère selon les segments des ménages.

Dans une deuxième partie du projet, nous avons utilisé les résultats et les données de la première analyse empirique pour développer un ensemble de modèles multi-agents qui décrivent le comportement d'investissement et d'utilisation des ménages dans les trois domaines énergétiques en tenant compte de la même segmentation des ménages développée dans la première partie du projet. Le modèle utilise les influences empiriquement trouvées de l'information, des normes sociales et des prix, ainsi que d'autres relations (par exemple, les effets de la confiance ou de la sensibilité à la pression des pairs) et est initialisé avec des données SHEDS (par exemple, concernant les stocks d'appareils électriques, possession de voitures, revenu, taille du ménage). De plus, les modèles capturent les interactions entre les ménages via des conversations qui transportent des informations et des normes

sociales dans différents réseaux de ménages (famille, amis, voisinage) et qui permettent de simuler les effets de campagnes basées sur des informations ou des normes. La structure de conversation a été calibrée à partir de données cantonales dans le domaine de la mobilité.

À l'aide de ce modèle, nous avons simulé différents scénarios, tels que l'introduction d'une taxe sur le CO2 de 200 CHF/t, des subventions sur des appareils efficients en énergie ou des véhicules électriques, ou des campagnes basées sur l'information et les normes sociales. Les résultats de ces simulations indiquent que l'information seule a un impact limité sur l'utilisation de l'énergie dans les trois domaines, mais que les campagnes sur les normes sociales ainsi que les incitations monétaires peuvent avoir des effets substantiels. En outre, les résultats suggèrent que les ménages diffèrent fortement en ce qui concerne leur réponse aux instruments souples, de sorte qu'il pourrait être utile de cibler des groupes de ménages spécifiques avec des campagnes. Enfin, nos scénarios indiquent qu'une utilisation combinée d'instruments monétaires et souples entraîne plus d'impact que de s'appuyer uniquement sur un seul instrument, mais qu'il s'agit d'une relation sous-additive, c'est-à-dire que l'utilisation combinée produit des effets plus faibles que la somme des effets séparés. Cela implique que la combinaison d'incitations douces et monétaires pourrait être utile, mais qu'une certaine éviction a lieu.

Dans l'ensemble, le projet a des implications pour les recherches futures ainsi que pour la mise en œuvre pratique. Pour la recherche, cela suggère que l'inclusion (au moins en partie) de l'hétérogénéité des ménages dans les modèles d'énergie-économique pourrait être bénéfique. Cette hétérogénéité ne doit de préférence pas être une hétérogénéité de revenus mais plutôt une hétérogénéité en termes de conditions de vie (rural vs urbain, jeune vs retraité). En outre, nos résultats indiquent qu'une inclusion plus large de mesures politiques souples dans les modèles de simulation d'énergie-économique pourrait être justifiée ; elles peuvent produire des impacts plus faibles que les incitations monétaires, mais elles ont un effet, même au niveau agrégé, et sont beaucoup moins controversées et donc plus faciles à mettre en œuvre.

En ce qui concerne la mise en œuvre pratique, nos résultats suggèrent qu'une utilisation ciblée d'instruments souples pourrait être utile. Nos résultats empiriques (et par conséquent aussi nos résultats de simulation) suggèrent fortement que les instruments souples n'ont d'effet que pour certains segments de la population globale. Ces segments pourraient être facilement identifiés et ciblés. Par conséquent, une analyse plus approfondie de la manière dont des mesures politiques souples pourraient être utilisées pour cibler des segments de population pourrait être justifiée.

Summary

In this project, we have analyzed the effects of information, social norms (injunctive and descriptive), and prices on household energy demand in the domains of electricity, heating (space and water), and mobility. The unique contribution of the project is the coupled use of an empirical analysis based on detailed survey data and model-based approach for aggregation and simulation.

For the empirical analysis, we use data from SHEDS (Swiss Household Energy Demand Survey), which provides information on investment and usage behavior of 5'000 Swiss households (representative for the German and French speaking regions of Switzerland) for 5 years for the three domains of energy use as well as detailed information on key characteristics of these households (e.g., socio-demographic data, attitudes and values, energy literacy, susceptibility to peer pressure and social norms, trust in different providers of energy-related information). Based on this data, we have estimated the influence of information, injunctive and descriptive norms, and prices on the investment and usage behavior of Swiss households for electricity, heat, and mobility. Furthermore, we have clustered the households into 5 segments according to age and place of living (rural vs urban). To see whether these household segments differ regarding their response to soft policy measures, we have re-estimated our models for these subsamples. Due to being based on only 5 years of observation (for the SHEDS data), the empirical analysis should be interpreted with care, that is, as showing correlations not "causal" effects.

This empirical analysis has shown first that information and social norms have significant correlations with energy-related household behavior, although the impacts might be comparatively small. Second, it has shown that the different household segments differ substantially in their behavioral response to information and social norms, that is, we have found strongly differing correlations between energy-related behavior and soft instruments for different household segments. Furthermore, the same holds for the three domains of energy use as well as between investment and usage behavior, resulting in a fairly complex overall picture of the influence of soft instruments on household energy use.

In a second step, we have verified these results with an independent data source (FOS data for Swiss municipalities) for the domain of mobility. This analysis supports the main conclusions from the first step, in particular, that soft instruments show a significant correlation with energy-related behavior and that this correlation differs between different household segments.

As a final part of our empirical analysis, we have conducted a choice experiment on home relocation (a setting of high importance for energy use that cannot be easily analyzed with survey data) that again supports the findings of the other empirical assessments that soft instruments have an effect and that this effect differs between segments of the population.

In a second part of the project, we have used the results and data from the first empirical analysis to develop a set of agent-based models that describe the investment and usage behavior of households in the three energy domains taking into account the same household segmentation developed in the first part of the project. The model uses the empirically found influences of information, social norms, and prices, as well as further relations (e.g., the effects of trust or susceptibility to peer pressure) and is initialized with SHEDS data (e.g., regarding stocks of electrical appliances, car ownership, income, household size). Furthermore, the models capture interactions among households via conversations that transport information and social norms in different household networks (family, friends, neighborhood) and that provide a way to simulate the effects of information- or norm-based campaigns. The conversation structure has been calibrated using cantonal data for the domain of mobility.

Using this model, we have simulated various scenarios, such as the introduction of a CO_2-tax of 200 CHF/t, subsidies on efficient appliances or electrical vehicles, or information- and norm-based campaigns. The results of these simulations indicate that information alone has a limited impact on energy use in all three domains, but that norm-based campaigns as well as monetary incentives can have substantial effects. Furthermore, the results suggest that households differ strongly regarding their response to soft instruments, so that targeting specific household groups with campaigns might be useful. Finally, our scenarios indicate that a combined use of monetary and soft instruments leads to more

impact than relying solely on a single instrument but that this is a sub-additive relation, that is, the combined use yields smaller effects than the sum of the effects of separate uses. This implies that combining soft and monetary incentives could be useful but that some crowding-out takes place.

Overall, the project has implications for future research as well as for practical implementation. For research, it suggests that including (at least some) household heterogeneity in energy-economic models could be beneficial. This heterogeneity should preferably not be income heterogeneity but rather heterogeneity with regard to living conditions (rural vs urban, young vs retired). Furthermore, our results indicate that a broader inclusion of soft policy measures in energy-economic simulation models might be warranted; they might yield smaller impacts than monetary incentives, but they have an effect, even in the aggregate, and are much less controversial and thus more easily implemented.

Regarding practical implementation, our results suggest that a targeted use of soft instruments might be useful. Our empirical results (and accordingly also our simulation results) strongly suggest that soft instruments have an effect only for some segments of the overall population. These segments could be easily identified and targeted. Consequently, a closer analysis how soft policy measures could be used to target population segments could be warranted.

Main findings

- Soft instruments, such as information and social norms, often have a negative correlation with household energy use, albeit the likely impact is smaller than for monetary incentives.
- Different segments of the Swiss population appear to respond differently to soft instruments and such instruments have also different effects for electricity, heating, and mobility, as indicated by strongly differing correlations between soft instruments and energy use for different household segments and different domains of energy use.
- This implies that a targeted approach for using soft instruments could be useful, that is, targeting specific population segments (e.g., young people living in a city) could already yield a substantial impact at much lower costs than a population-wide campaign.
- Our results also indicate that including some level of heterogeneity of households in energy-economic models as well as covering soft instruments in addition to monetary incentives could provide a better basis for future policy assessments.

Acknowledgement

We would like to thank the colleagues Prof. Dr. Miguel Brendl (University of Basel), Prof. Dr. Paul Burger (University of Basel), Prof. Dr. Heinz Gutscher (University of Zurich), and Prof. Dr. Jens Köhrsen (University of Basel) for their support and their contributions to the expert panel on social norms that accompanied this project.

Contents

Abbreviations

ABM – Agent-based model

Cl – Cluster

CREST - The Competence Center for Research in Energy, Society and Transition

Desc – Descriptive

EA – Electrical appliance

EEA – Energy-efficient appliance

ElCom – Federal Electricity Commission

EU - Electricity Usage

FEDRO – Federal Roads Office

FSO – Federal Statistical Office

GA – General Abonnement

HH – Household

HTA – Half Fare Travelcard

Inf – Information

Inj – Injuctive

Lit – Literacy

Max – Maximum

Min - Minimum

MoT – Mode of Transport

nl - non-linear

NW – Network

Obs - Observation

PSEEA - Preferred share EEA

RA – Regional Abonnement

SBB – Schweizerische Bundesbahnen

SCCER – The Swiss Competence Centers for Energy Research

SFOE – Swiss Federal Office of Energy

SHEDS – Swiss Household Energy Demand Survey

SN - Social Norms

Std. Dev. - Standard Deviation

1 Introduction

1.1 Background information and current situation

Reducing energy demand will be central for the achievement of the Swiss Energy Strategy 2050 targets. To reduce energy consumption per capita, altering 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 is 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 aspects need to be considered when focusing on soft incentives: (1) the heterogeneity of household responses to soft measures, and consequentially (2), the aggregate effects, that is, to what extent soft measures alter the total energy consumption of all Swiss households. These aspects are linked: If households respond differently to soft measures, it is not clear how information is diffusing in society and how social norms are altered by campaigns, so that aggregate effects are not easily deduced from an analysis of individual behavior. To work on both aspects, 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.

We use survey data on the individual level as the main basis of our empirical analysis and our model. Using this data, we 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. To aggregate the individual responses, we develop an agent-based model that uses the empirical results to describe individual behavior, taking into account feedback effects from changes to social norms and information diffusion. Finally, we cross-check our analysis with municipal data for mobility.

The project was embedded in SCCER CREST and helped 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 complemented the development of a detailed demand-side model within CREST. The project utilized the basic structure of the model developed in CREST (description of different types of energy use and different types of households) but extended it to cover information and social norms in addition to the standard policies (such as prices).

1.3 Objectives

The project is structured along an empirical and a model-based stream with respective objectives. We first investigate (based on survey data) how strongly perceived pressure from social norms, energy literacy, and energy prices influence energy-related behavior and whether these influences differ among different socio-demographic groups (clusters[1]). The results show that there is indeed heterogeneity across clusters and across the three energy demand types (electricity, heat, mobility). This indicates that there could be a benefit of tailoring policy interventions to particular subgroups of the Swiss population.

Second, we use the insights of the empirical 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 in the three domains of energy use (electricity, heat, mobility) and to compare both monetary and soft incentive policy approaches as well as targeted and non-targeted policy measures.

[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

Given the complexity of the research question and the different approaches required for tackling the data and model-based aspects, the project consists of two parallel streams:

- **Workstream 1 "Empirical Analysis":**

  Within WS1 the influence of information and social norms on different types of energy use for different types of households is analyzed, using the CREST household survey SHEDS (individual level analysis) as well as municipal data (municipal level analysis) on mobility.

- **Workstream 2 "Agent-based modelling"**

  Within WS2 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 is developed and policy scenarios are simulated.

The empirical insights derived in WS1 are interlinked with the model in WS2 along two dimensions. On the one hand, the insights on literary, norms and general household behavior serve as the main basis for describing the decision processes within the agent-based model (blue elements in Figure 1). On the other hand, the gathered survey and municipal and cantonal data and empirical results provide the household characteristics and external data used to initialize and calibrate the agent-based model (green elements in Figure 1).

In the following subsections, we will provide an overview of the empirical approaches and data sets of WS 1 (Section 2.1) and the basic agent-based model design and functionality (Section 2.2). The transfer of insights and data between WS1 and WS2 is presented in Section 2.3.

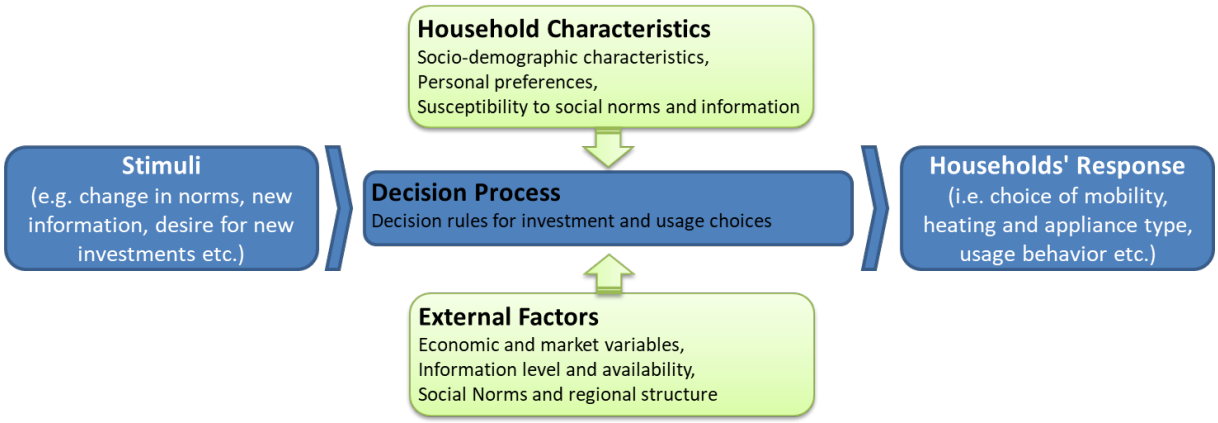


Figure 1: Generic structure of model setting and data inputs

2.1 Workstream 1 “Empirical Analysis”

The empirical assessment in Workstream 1 serves to identify drivers for energy-related decisions and behavior of Swiss households building upon the Swiss Household Energy Data Survey (SHEDS) and municipality data. We describe the data and methods first at the individual level (Section 2.1.1) and then at the municipal level (Section 2.1.2). Given the available data (small number of waves in SHEDS, cross-section data in the analysis of municipal data), it is important to stress that our approach can only aim at identifying correlations between individual characteristics, policy instruments, and energy-related behavior. To ascertain that these correlations can be interpreted as an instrument or personal characteristic having an effect on energy use requires additional information that was not available for this project (e.g., panel data with much more than 5 years of observation). For the purpose of developing the agent-based model (Workstream 2), we use the empirical results as if they could be interpreted as effects, but it should be clear that this is an assumption not a result of the empirical analysis.

2.1.1 Empirical analysis: Individual level

For the empirical analysis of the relationship between energy literacy, social norms and household energy consumption, we use data from the Swiss Household Energy Demand Survey (SHEDS).[2] SHEDS is an annually conducted longitudinal household survey with a sample that is representative of the population of the German and French speaking regions of Switzerland with regard to age, gender, language region and living situation (home ownership) (Weber et al. 2017). It covers household energy consumption (investment and usage) in the areas of electricity, heating (space and water) and mobility as well as various household characteristics, psychological information, and social context. As the survey is a rolling household panel with new respondents being added each year, we pool the data of five survey waves from 2016 to 2020 and conduct a cross-sectional analysis using year fixed effects. The sample thus covers 11’291 unique respondents.

The empirical analysis of the SHEDS data at the individual level is the foundation for the agent-based model, which we employ to analyze household behavior on the aggregate level. We assess various investment and usage behaviors for the three energy areas electricity, heating and mobility. The main hypothesis that we investigate is that there is a positive relation between energy-conserving behavior and energy literacy as well as social norms. The second hypothesis that we investigate is that these relations differ between different types of households (clusters). In general, the estimation models can be described by:

$$Y_{i,e} = F\left(\alpha + \beta X_i + \gamma Z_{i,e} + \theta T_i + \varepsilon\right), \qquad \text{(S1)}$$

where:

- $Y_{i,e}$ is the energy-related behavior of respondent *i* in energy area *e*.
- X_i describes individual and household specific socio-economic information.
- $Z_{i,e}$ summarizes other individual and household information as well as price information (where applicable) that is specific to an energy area.
- T_i includes our explanatory variables of interest: energy literacy and social norms:
    - Our measure of energy literacy is an index ranging from 0 to 11 constructed from multiple questions in SHEDS that test the energy-related knowledge of respondents (see Appendix 10.1). Each correct answer is assigned the value 1, each incorrect answer the value 0. All answers are then added up to form the literacy index. The higher the value of the index, the higher is a person’s energy literacy. The design of this index is based on previous work by Blasch et al. (2017).

[2] The questionnaire can be found at https://www.sccer-crest.ch/research/swiss-household-energy-demand-survey-sheds/.

- Social norms are measured by questions asking about perceived injunctive and descriptive norms. Injunctive norms describe what behavior is socially approved or disapproved of (Cialdini et al., 1991). In our analysis, injunctive norms refer to whether the respondent perceives peers to expect the respondent to behave in an environmentally friendly manner. Descriptive norms reflect perceived environmentally friendly behavior of peers. Susceptibility to the two norm specifications is 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.

- F is the link function of the respective model.

All X_i and $Z_{i,e}$ covariates as well as the type of estimation model (F) are reported in Appendix 10.3. The pooled SHEDS data is used as cross-sectional data, and for each estimation model, the first available data point per respondent that covers the variables of interest (dependent variable, energy literacy, social norms) are used. The largest possible sample size for the analysis is 7'724 and smaller than the original 11'291 respondents, because the social norms questions changed between 2016 and 2017. Thus, respondents who only participated in 2016 drop out. Because of missing data for some variables and respondents, the sample size further differs with each estimation model (see estimation results in Section 3.1.1, Appendix 10.2 and Appendix 10.4 for the respective sample sizes). The models of energy behavior are estimated for the full sample and individually for different household segments (clusters) in order to have household type-specific correlations between behavior and soft measures. Descriptive statistics of socio-economic variables as well as energy literacy and social norms are available in Appendix 10.3.

Price elasticity

In SHEDS, participants state electricity prices based on their electricity bills if possible. Based on the recorded responses however, this was a difficult task. To improve the quality of the data, we use publicly available electricity price data that is published by ElCom. We match prices for standard electricity tariffs with respondents in the SHEDS based on zip codes and the household classification key used by ElCom. The subsample of 1'114 SHEDS participants, for which we can match the price data, consists of households with a standard electricity tariff, and which live in municipalities with a single electricity provider. To estimate price elasticities for this subsample, we model the logarithm of the stated electricity usage (bill-based) as a function of the logarithm of the total energy price, sociodemographic and household-specific control variables.[3]

Household segmentation

To analyze heterogeneity across households in relation to soft measures, we distinguish different types of households. Thereby, our segmentation approach is chosen to satisfy two criteria. First, it has to capture distinct life situations. Second, it is built to be potentially useful in practice, that is, it relies solely on easily observable household characteristics. After examining a multitude of different approaches for household segmentation, we segment households by age[4] and the spatial place of living (see Table 1). The first two segments describe young households between the age of 20 and 39.[5] Segment 1 includes households in urban areas whereas Segment 2 includes households in rural areas (agglomeration and countryside). Segments 3 and 4 describe mid-age households (age 40-64) in urban and rural areas

[3] The sample size for this estimation is small since only a small share of the SHEDS sample states the electricity usage based on the bill instead of a best guess.

[4] To segment households by age, we consider the age of the respondent. As only people that are at least partially responsible for the household answer the survey, age in the segmentation thus reflects the age of the household decision maker.

[5] The words "segment" and "cluster" will be used interchangeably.

respectively. Segment 5 is formed by senior households with no spatial distinction. Altogether, this approach has proven to be highly useful in our analysis and is based solely on easily discernible criteria, which facilitates using this approach as a basis for targeted policy measures.

Table 1: Household Segmentation by age and the spatial location

		Place of living	
		Urban	**Rural**
Age (years)	**20 - 39**	Segment 1	Segment 2
	40 - 64	Segment 3	Segment 4
	65 +	Segment 5	

Discrete choice experiment: Home relocation[6]

In addition to the base data of SHEDS as described above, SHEDS also contains a set of choice experiments that differ between waves to address specific topical aspects for which the normal survey structure is insufficient. Within the project we conducted one such experiment to gain additional insights into a highly relevant part of individual behavior, namely home relocation. As such relocations occur too rarely to be readily observable in a mid-scale survey, such as SHEDS, a randomized controlled discrete choice experiment was used 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.[7]

The purpose of this experiment has been twofold: First, we wanted to investigate whether the main insights from the analysis of the SHEDS data hold up if we consider structural components of energy demand (as, e.g., the place of living, commuting distance, household size). Thus, the experiment serves as an indication to what extent our insights can be extrapolated to questions outside the scope of this project. Second, the experiment provides data for possible future extensions of the agent-based model, where agents can adjust the structural components of their energy demand. We first envisioned such an extension in the context of this project (in addition to the planned work of the application). However, this has proven to be infeasible, as home relocation requires an integration of at least two of the different agent-based models (heat and mobility), which (despite the similar structure of the models) was not achievable in the given timeframe.

The choice setting of the home relocation allows us to 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 certain 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 the energy demand. The larger the living space is 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. Furthermore, as a third home-related aspect, the home location affects energy demand for mobility. 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 given the preferred mode of transport.

[6] Details can be found in the working paper Velvart et al. (2022): Link

[7] The experiment was designed in collaboration with other CREST researchers (see Section 7).

The experiment ran in the 2019 wave of SHEDS. 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 which housing characteristics others have generally chosen as well as which choices are socially approved of (energy-conserving options). 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. Then, participants faced six choice sets in which they chose between two housing options (see Figure 2 for an example). The options differed in the three attributes living space size, energy efficiency, and implied commuting distance. Pricing information, which reflected current market prices, was also provided.

For the analysis of the experiment, we use a structural approach and model discrete choices by building on the random utility maximization framework. Explanatory variables for the choice probabilities of housing options shown to participants are the three housing attributes. The effect of the treatments is modelled in interaction with each attribute. As we are interested in behavioral differences across household types in reaction to the treatments, we estimate mixed logit models separately for the full sample as well as for individual household segments. We segment households according to our segmentation strategy given in Table 1. Each of our five household types is well represented in the sample with at least 50 respondents within each control and treatment group.

Which of the two housing options do you prefer?

Please note: You can receive additional information by moving the mouse cursor to the characteristics of the housing options.

	Option A	**Option B**
Size of the living space	80 m^2	120 m^2
Energy efficiency	high	low
Distance to frequently visited places	long	long
Price in CHF (rent / buy)	1'456 / 491'700	1'853 / 656'280

Figure 2: Example of choice set for the home relocation experiment

2.1.2 Empirical analysis: municipal level

The empirical analysis at the municipal level has two purposes. First, it serves of a check of the main insights of the above-described analysis of the SHEDS data with a completely independent data set that is built on observations not stated behavior as SHEDS. In particular, the questions are analyzed whether norms and information do have an effect on behavior and whether this effect differs between different types of municipalities, which are built to resemble the clusters used in the SHEDS-based analysis. Second, a similar data source (FOS mobility data on a cantonal level) is used to calibrate those elements of the agent-based model that cannot be informed by SHEDS data, in particular, the conversations in household networks.[8]

As only data for mobility-related behavior is available on the municipal level, the cross-check and calibration are done for this domain of energy use. We have collected three types of data: (i) socio-demographic and economic characteristics, (ii) mobility behavior, and (iii) proxies for social norms and information.

We analyze the investment behaviors for mobility at the municipality level. Like the empirical analysis at the individual level, we investigate whether there is a positive relationship between mobility behavior and information as well as social norms. Furthermore, we explore whether these relations are different between different types of municipalities (clusters). For the full sample and cluster estimation, we use the following model:

$$Y_i = F(\alpha + \beta X_i + \gamma Z_i + \varepsilon), \qquad \text{(ML1)}$$

where:

- Y_i is the mobility behavior of the municipality *i*.
- X_i describes the control variables that include socio-demographic and economic characteristics of the municipality *i* and the cantonal fixed effects.
- Z_i represents the explanatory variables of interest: proxies for information and social norms for the municipality *i*.

Socio-demographic and economic characteristics

To allow a linkage between municipality data and SHEDS results, a matching needs to be established. To this end, the clustering approach defined in Section 2.1.1 is transferred to the municipal setting. The required socio-demographic and economic data on municipality level are provided by the Swiss Federal Statistical Office (FSO). Using the municipality characteristics regarding age distribution and spatial typology, we apply the same clustering approach as in the previous analysis on the SHEDS data. For the age distribution we use the dominant group within a municipality when their percentage is higher than the mean of the full sample. The resulting age distribution is consistent with the age distribution in the SHEDS data (see Table 2). For the segmentation, we combine the age distribution with spatial typology to obtain the five clusters. The resulting cluster distribution is also consistent with the one in the SHEDS data analysis (see Table 3).

[8] We had to use the cantonal level for the calibration, as the SHEDS dataset, which is the basis for the agent-based model, is too small to calibrate on the municipal level; there are simply too many municipalities with no or only a few respondents in SHEDS.

Table 2: Age distribution based on dominant group

		SHEDS		Municipality	
		Number	Percent	Number	Percent
Age (years)	**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 3: Clustering

		SHEDS		Municipality	
		Number	Percent	Number	Percent
Cluster	**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

Municipal mobility data

The mobility data covers both, information on public and on private transport. The respective data has been provided by the Schweizerische Bundesbahnen (SBB) and the Swiss Federal Roads Office (FEDRO). In detail, we use the following variables:

- GA travel cards and half fare travel cards (HTA) per 1000 citizens
- Total cars per 1000 inhabitants and share of e-cars and hybrid cars
- Share of cars with efficiency type A to type G, respectively

Proxies for social norms and information

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.[9] Regarding social norms at the municipal level, we have considered three indicators as proxies for social norms:

- The first indicator is based on vote for Green Party during the national election in 2015.
- The second indicator considers the environmental ballot “Energy Law: LEne” that took place on the 21st Mai, 2017. This indicator is an alternative proxy of green ideology and is less influenced by elections events.

[9] 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, and employment).

- The third indicator focuses on green business (organic bread) in shops. 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 or green businesses would be more likely to locate near green community (Kahn, 2007)

FSO has provided data on the voting behavior during elections (first indicator) and environmental ballots (second indicator). For the green business data (third indicator), we collected data on the availability of green products selected Migros shops, as this information is available online. For time consistency, the online data has been collected in two rounds. The first and second round took place in February-March 2019 and June 2019, respectively. We have considered two types of organic products (eggs and bread) as they are the most bought ones in Switzerland (Bio Suisse, 2019). In each Migros shop, we have checked online if the product is available. In addition, whenever we have the information, we have checked how many of the products are still available in the selected shops.

In order to be consistent with the argument of using green business as a proxy for social norms, we have extended this indicator to municipalities where a Migros shop is not available. Even though a municipality does not have a Migros shop, someone living in a close municipality with a Migros shop can have access to the green products depending on the distance. Consequently, for any municipality without Migros shops, we have calculated the weighted average of the availability or quantity of selected organic foods using the distance to the three closest Migros shops.

As a proxy for information (energy literacy), we use information on the availability of LED light bulbs in Migros shops. We consider this to be related to energy literacy, as such light bulbs are economically more efficient than traditional ones, so that choosing an LED light bulb is not an expression of environmentally friendly attitude but rather of being informed about energy topics. We have collected online information on LED light bulbs in Migros shops, as described above. The information includes both the availability and quantity of the LED light bulbs in each shop. We have also extended the information to the other municipalities without Migros shops following the same approach as described above.

We use the proxies for information and social norms in the municipal level analysis, as independent variables together with socio-demographic and economic characteristics. As dependent variables, we use the variables from the municipal mobility data.

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 behavior of consumer agents who are influenced by social norms, information, and policy interventions (see Figure 1). To this end, an agent-based model has been designed that captures the basic investment and usage decisions of individual households with respect to electricity, heat, and mobility. Furthermore, agents in this model interact via conversations and norms, so that the aggregate model results can potentially differ from a simple aggregation of individual results (due to positive feedback effects, such as the diffusion of information or a change of social norms). In the following, the model structure is described using the electricity model as an example (see Section 2.2.1), as the electricity ABM is used as the main blueprint for the heat and mobility models. Subsequently, the differences to the heat and mobility models are illustrated (see Sections 2.2.2 and 2.2.3, respectively). The model code is available at https://fonew.unibas.ch/de/research/energy-modeling/.

2.2.1 Model structure and electricity ABM

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. Three agent-based models are developed for electricity, heat, and mobility. The three models follow the same overall structure (Figure 3), differing mainly in the investment and usage variables (highlighted in red in Figure 3 for the example of electricity).

Each model starts with the ***initialization*** and parameterization of the agent population (households and/or individuals) for which the empirical data of WS1 is utilized. The initialization is performed once, so that it does not change in the following simulation, that is, it represents the starting endowment of the households. The ***simulation*** determines the respective agent behavior 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 aggregated and ***reported*** in different resolutions.

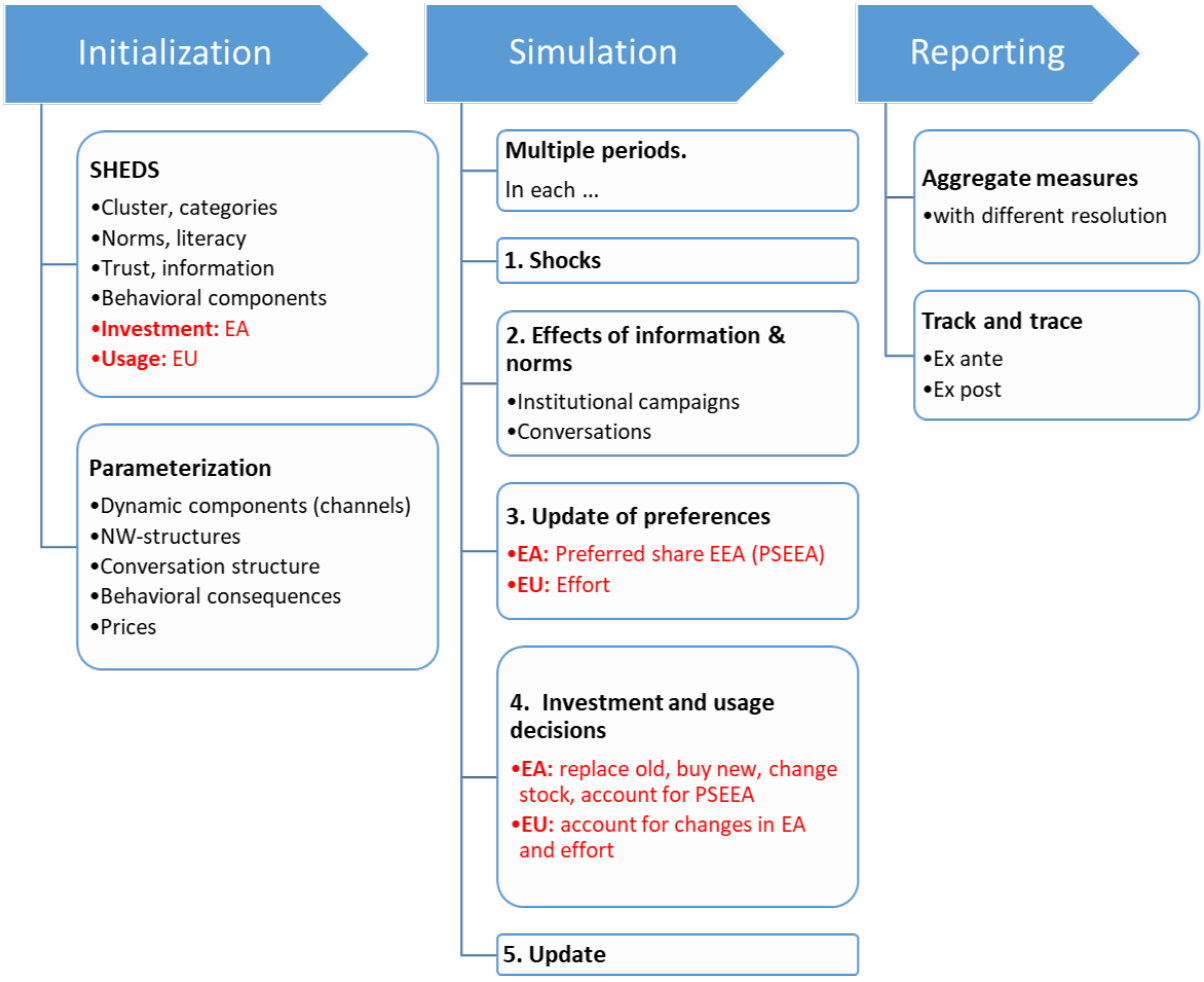


Figure 3: Structure of agent-based models using the example of the electricity model.

Initialization

The agent population of the models is based on the SHEDS providing detailed information on consumption and usage decisions for electricity, mobility, and heat. Agents in the agent-based model (ABM) mimic the SHEDS population whenever possible. For electricity, the sample includes 6'579 households.[10] The households are segmented into the five clusters (Table 4) according to age and location as explained in Section 2.1.1.

This basic household clustering is also applied for the heating and mobility models (but with small differences in sample size in the heating and mobility model). 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)

The clusters and categories are used in the ABM to account for the differences between the household types observed in SHEDS in the initialization of the data (as well as in the presentation of results). Whereas the cluster definition remains unchanged across all three models, the categorization changes for the mobility model (see section 2.2.3 on mobility ABM). In addition to the clusters and categories, households are classified by canton and language region (German and French).

Table 4: Agent distribution of the electricity ABM

	Definition	Number of HHs/ Agents
Cluster 1	young city	1'649
Cluster 2	young agglo & country	1'281
Cluster 3	middle-old city	1'211
Cluster 4	middle-old agglo & country	1'570
Cluster 5	old city & agglo & country	868
	Total	6'579

The agents are initialized based on cluster- or cluster- and category-specific conditional probabilities. From SHEDS, each agent is assigned character traits that include 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. Table 5 gives an overview of the respective variables, which scale they have and from which SHEDS question they were derived.

[10] The number of households is smaller than the approx. 11'000 observations from SHEDS, since the latest survey from 2020 was no longer included. In addition, people from 2016 are not included, if they did not participate in later years, as there were other social norms questions in 2016.

Table 5: Overview of selected variables

Variable	**Scale (steps)**	**Derived from the following SHEDS question:**
Descriptive norms	1 (totally disagree) – 5 (totally agree) (1)	I believe that most of my acquaintances behave in an environmentally friendly manner whenever it is possible.
Injunctive norms	1 (totally disagree) - 5 (totally agree) (0.5)	Average of: The members in my household expect that I behave in an environmentally friendly manner. Most of my acquaintances expect that I behave in an environmentally friendly manner.
Literacy	0-11 (1)	see Appendix 10.1
Trust in: - Family - Neighborhood - SFOE - Utility	1 (not at all) - 5 (very strongly) (1)	Regarding energy and saving energy, how strongly do you trust information provided by the following people? *- Family, friends, or colleagues* *- Neighbors* *- SFOE* *- Local energy supply utility*
Info from: - Family - Neighborhood - SFOE - Utility	0 (no),1 (yes)	From whom have you already taken up recommendation for changing your energy consumption? *- Family, friends, or colleagues* *- Neighbors* *- SFOE* *- Local energy supply utility*
Effort	1 (very unlikely) - 5 (very likely) (1) *Translated (linear) to:* 1 (very unlikely) = 1 5 (very likely) = 0.7	In the next 12 months, are you planning on reducing your electricity consumption?

The norms, literacy, and trust variables are all categorical variables, each representing a range from low to high. For the information channels, each agent is assigned a binary number for each channel, which is one if the agent has already used a particular information channel according to the SHEDS survey. While norm levels, information channels, and trust values remain unchanged over the course of the simulation the literacy level may change. Figure 4 shows the (initial) distribution of norms and information (for the SFOE channel only) values over all households.

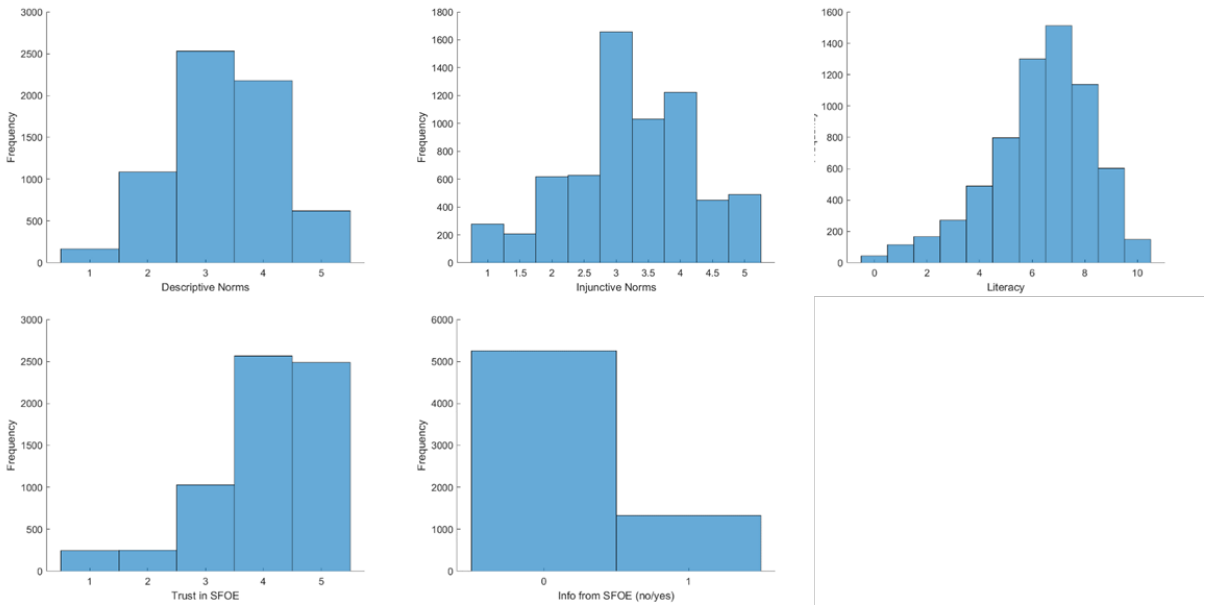


Figure 4: Norms and information distributions.

In terms of norms (descriptive and injunctive), the majority of households tend to be located in the middle (i.e. a norms level between 3 and 4). For literacy, the distribution is to the right, i.e. many households have a rather high literacy level (greater than 6). As with literacy, the distribution of trust in the SFOE is right-sided, so household trust in the SFOE is generally high. At the same time, only a few households have taken up information from the SFOE in the past (approximately 20%).

Each agent is assigned model-specific behavioral components (preferences) as well as investment and usage variables. In the simulation phase, behavioral variables can be influenced by norms and information channels, such as conversations, network effects, or institutional campaigns, but also by price changes (see Section Simulation). The changed behavioral variables have an impact on purchase (investment phase) or utilization (usage phase) decisions in subsequent periods.

In the ABM for electricity, agents decide on investments in electrical appliances (EA) and the associated electricity usage (EU). In the initialization phase, the agents are equipped with their initial EA and EU values and the corresponding preferences from SHEDS. 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 assignment of the EA stock to households is based on a cluster- or cluster- and category-specific normal distribution derived from SHEDS. 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 (see Section 2.3.1). Otherwise, we use the observed SHEDS data.

In addition to the stock variables, actors also have preferences for energy-efficient appliances. In the electricity model, the preference for EEAs is expressed by a household's preferred share of EEAs. In the initialization, the preferred share is assumed to be the observed EEA share for each household but

is corrected for the fact that labels were introduced relatively recently. Because of this effect, an agent's observed share may still be lower than its preferred share. On average across all households, the stock of large electric appliances is 4.85 units, of which 3.08 units are labeled efficient, resulting in an average EEA Share of 0.72 (see also Figure 5 for additional distributional details).

Regarding electricity usage, the behavioral component of agents is expressed in terms of households' effort to reduce their electricity consumption. Whereas the effort level derived from SHEDS is measured on a scale from 1 (low) to 5 (high), we transfer it linearly to a scale from 0.7 to 1 (see also Table 5). 0.7 corresponds to a value of 5, the highest effort level. Thus, we assume that a household can reduce its energy usage by up to 30% by increasing its effort. We make this transformation because effort is multiplied by the usage level (see below), where a higher effort should lead to a larger reduction in the usage level. The initial effort, which is on average 0.85, is assigned to the households taking into account correlation with norms and information in addition to differences between clusters (see Section 2.3.1). The same also applies to the initial electricity usage level. However, in order to make the level of electricity usage dependent on the stock and type of appliances, as well as on the efforts of the agents to reduce their consumption, a production function (Eq. 3E1) is defined: The average initial EU value is 2'354 KWh/a, the distribution is shown in Figure 5.

$$EU_h = EEA_h * base_{EEA} * Effort_h * Calib_h + (EA_h - EEA_h) * base_{NonEEA} * Effort_h * Calib_h, \quad \text{(E1)}$$

where:

- EU_h is the energy usage of household h (kWh/a).
- EA_h is the stock large electric appliances of household h.
- EEA_h is the stock large efficient electric appliances of household h.
- $base$ is the base consumption for efficient or non-efficient appliances.
- $Effort_h$ is the effort of households h to reduce its energy usage [0,1].
- $Calib_h$ is the calibration factor of households h. It is calculated by the difference between the EU level from SHEDS and the EU function for each household h.

For this, the usage level from SHEDS as well as the appliance stock was used to derive the base load (consumption per device) for EEAs and Non-EEAs. For each household, this base load (differentiated by efficient and non-efficient appliances) is then multiplied by the household's corresponding appliance stock and its effort. The deviation from this product and the household specific EU level from SHEDS is captured in a calibration factor that is defined individually for each household. The calibration factor thus covers elements not considered in the ABM, such as the exact number of persons in each household. It is calculated only in the initialization and remains fixed within the simulation. The average initial EU value is 2'354 kWh/a, the distribution is shown in Figure 5.

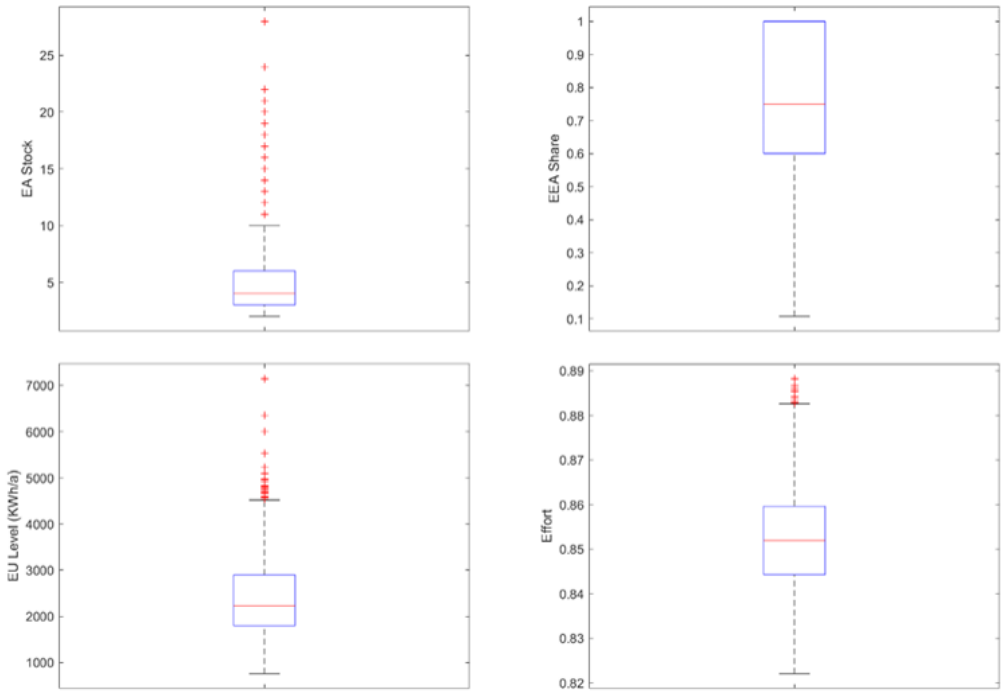


Figure 5: Boxplots of initial EA stock, EEA share, EU level and effort for the electricity ABM.

So far, the data association has been limited to agent specific data. In the next step of the initialization the dynamic model components and networks are defined in which the agents are connected to each other. Regarding network structures, three network types are considered (Figure 6):

- Family network: which include agents across all age groups and locations
- Friend network: which is limited to the similar age group
- Neighborhood network: which is limited to the same location

Further segmentation, for example by social norms, trust, and literacy in network formation, can be activated but was not applied in this project. However, during model calibration (see Section 2.3.2) it became apparent that a distinction by language regions (French and German) plays an important role in the exchange of agents, which is why it is also taken into account in the formation of networks. The networks are thus created separately for each language region, but an exchange across language regions still takes place in the conversations, as conversations take place not only in the networks but also between randomly selected agents. In addition to the networks, the conversation structures are established. These can be flexibly adapted in the simulations.

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 (specified in the Section on Simulation and Sections 2.2.2 and 2.3.2).

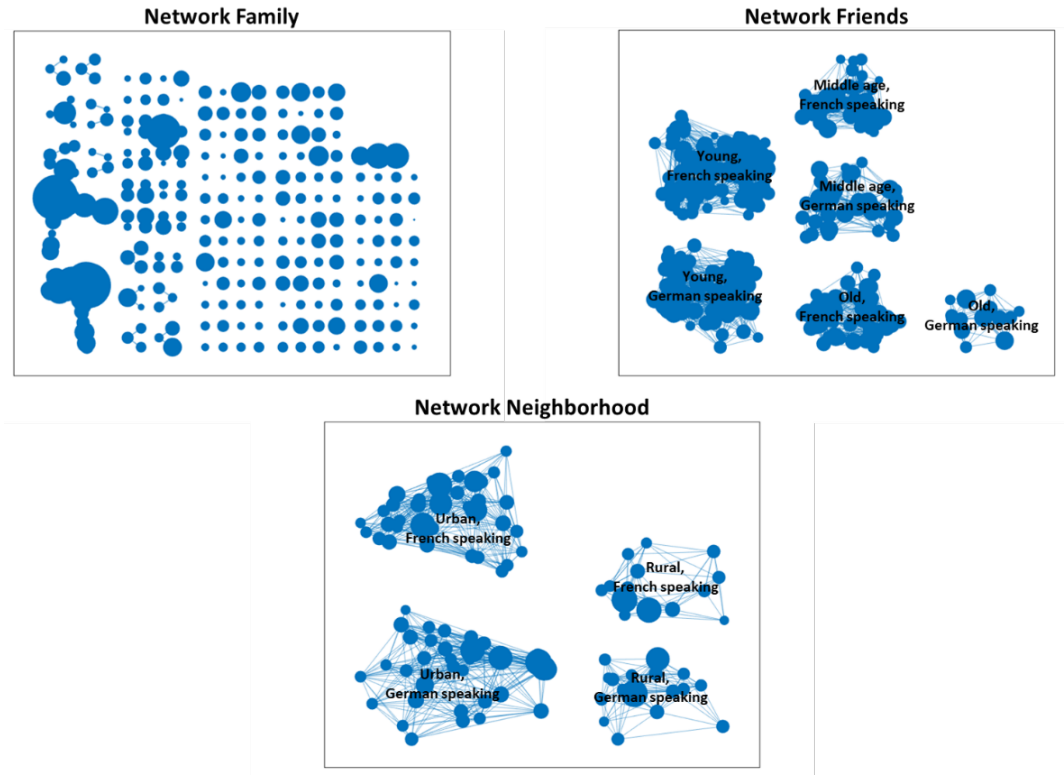


Figure 6: Family, Friends and Neighborhood Networks.

Simulation

After the initialization, the iterative decision processes of the agents for multiple periods (years) is simulated. In the electricity ABM, 10 years are simulated for each scenario. To obtain stable results, the simulation of each scenario is repeated several times (here 40 repetitions of each scenario). In all simulations, we differentiate between behavioral variables (preferences) 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 allows us to include random deviations from planned behavior, which is essential for maintaining a heterogeneous population of agents in the model.

The simulations have a predefined sequence and individual channels, and modules can be activated or deactivated. As depicted in Figure 3 for each period first external ***shocks*** (such as price shocks triggered e.g., by a subsidy or tax, in a predefined period) are accounted followed by the impact of ***institutional campaigns*** and ***conversations*** across the agents. Based on those impacts the agents' preferences are ***updated*** and the resulting ***investment and usage decisions*** are carried out.

On central element of the ABM is the impact of norms and information on the respective agents as well as the interaction across agents. At the beginning of each simulation period, we allow for campaigns by different institutions (SFOE, local utility) that can either create injunctive or descriptive norm pressure. ***Norm campaigns*** can take place once or in several periods. Within the ABM norms (injunctive or descriptive) serve as a channel through which institutions try to address the agents. Whether and to what extend a campaign reaches an agent depends on two characteristics: i) on the agent's norm level and ii) on his/ her trust in the sending institution (optionally, it could also be considered here, whether a household has already taken up information from the sending institution). From these two variables, the model derives the aggregate impact strength of a campaign on an agent, with five impact levels (full

strength of 1 if, for example, both the agent's norm level and trust in the institution are high, to no impact of 0 if both variables are low). A campaign is designed to address a specific target variable (e.g., the EEA Share) that has to be defined in the model together with a reference variable (e.g. average EEA share of the top 20 percent). For each household, the change in the target variable due to the campaign is calculated by multiplying the difference between the reference variable and the target variable by the household-specific impact strength. It is also possible to define whether only positive, negative or all changes in the target variables are taken into account.

In addition to norms campaigns, institutions can also launch one-year or multi-year literacy campaigns. ***Literacy campaigns*** are designed similarly to norm campaigns. However, compared to norm campaigns, literacy campaigns do not directly address a target variable, but the literacy level of households may change as a result of a campaign. If a correlation was observed in the SHEDS data, a change in literacy may subsequently have an impact on other variables (e.g., preferred EEA share). The strength of the literacy campaign on an agent depends on the agent's trust in the institution: The higher the trust in the respective institution, the stronger the campaign (Eq. L1). Whether a campaign has an effect, however, also depends on whether an agent has already taken up information from the institution in the past. If so, the change in literacy can be based on a reference value (Eq. L2), such as the average literacy level of all households, or the literacy level changes by a certain predefined percentage.

$$Strength_h = \begin{cases} 2, & if\ Trust_h = MaxTrust, \\ 1, & if\ 0.75 * MaxTrust < Trust_h < MaxTrust, \\ 0.5, & if\ 0.5 * MaxTrust < Trust_h \leq 0.75 * MaxTrust, \\ 0, & otherwise. \end{cases} \quad \text{(L1)}$$

$$\Delta Literacy_h = Strength_h * InfoFrom_h * (Reference - Literacy_h), \quad \text{(L2)}$$

where:

- $Strength_h$ is the strength of the literacy campaign for household h. The values (2, 1, 0.5) are own assumption, can also be defined differently.
- $MaxTrust$ is the maximum trust level over all households (which is 5 in our case).
- $\Delta Literacy_h$ is the change in literacy for household h. We assume: $0 \leq \Delta Literacy_h \leq 3$.
- $InfoFrom_h$ defines if households h has already taken up information from institution (0 = no, 1 = yes).
- $Reference$ is the reference literacy level. In our case, this corresponds to the average literacy level over all households.

After the campaigns, ***conversations*** between agents take place. In the course of conversations, agents select a predefined number of conversation partners from their networks (family, friends, and neighborhood) as well as random additional agents (cluster-specific selection would also be possible). Afterwards, the design of the conversations is determined. The central aspect of conversation is the relevant topic (see Figure 7). The topics of a conversation can be model-specific, that is, electrical appliances (EA) or electricity consumption (EU) in the electricity model. There is also the possibility of learning in the context of the conversation and due to the way conversations work, learning (Info) is also defined as a topic. However, the conversations can also be completely unrelated to energy (which is the case in 70% of the conversations in the ABM), where the conversation has no influence on behavior.

After selecting the conversation partners and determining the topic of conversation, the next step is to determine the potential direction of influence (i.e., which conversation partner influences whom). Figure 8 shows an example for one agent: over all years (9 in this example), the agent has five conversations on the topic of electrical appliances in his/ her friends network in which he/ she influences his/her conversation partner (direct successor represented by a large blue dot). In addition, the agent has one

conversation on the topic of EA in which he/she is influenced by his/ her conversation partner (direct predecessor represented by a large black dot). The next level of influence (predecessor of the predecessor and successor of the successor) is also shown in the figure. However, these agents have no direct influence on the selected agent (but on the conversation partners of the selected agent by being influenced by them or influencing them). As shown in the table below Figure 8, the direction of influence can depend on the trust of the agents in a network (here the friends network). If there is a significant difference (>1) between the trust levels of the agents, the agent with the higher trust level will be influenced by the other in the conversation. Furthermore, the conversations are intended to represent the role of social norms in the interaction with other agents. Therefore, in addition to the trust of the agents, the level of injunctive norms is also considered in determining the direction of influence. If there is no significant difference in the level of trust (≤1) or if the difference in the level of injunctive norms is higher, then the level of injunctive norms determines the direction, while the agent who feels the higher norm pressure (i.e., has the higher injunctive norms as derived by SHEDS) adjusts his/ her preferences (for electrical appliances or electricity consumption, depending on the topic of the conversation). If the difference between both, the trust levels, and the norms, is not significant (<=1), the direction of the influence is randomized.

In addition to the social norm channel (social norm pressure), there is also the possibility that agents learn from each other in the conversations (if the topic is Info) and thus change their literacy level (information channel). In this case, the direction of influence is not determined by the norms level as before but, in addition to trust, by a comparison of the literacy level of the conversation partners. To this end, we assume that the agent with the lower literacy level learns from the one with the higher literacy level (was also tested in the model calibration). Regarding the information channel, another way in which institutional campaigns are represented in the model is that the campaign addresses the diffusion of information. Therefore, in the model, a campaign (norms or literacy campaign) leads to an increase in the probability of talking about a certain topic.

The agent that finally adjusts its preferences (or its literacy level) in the conversations does this by partially adjusting its own preference (or its literacy level) to that of the other party (as shown in Eq. C1). The extent ($Weight$) of the adjustment was determined in the model calibration. In general, we have many degrees of freedom in how the conversation is designed or structured. However, since the design of the conversations must be determined in advance and should remain the same in all scenarios, it was tested and fixed in the course of the model calibration (see Section 2.3).

$$Preference_{Agent1} = Weight * Preference_{Agent2} + (1 - Weight) * Preference_{Agent1}. \quad \text{(C1)}$$

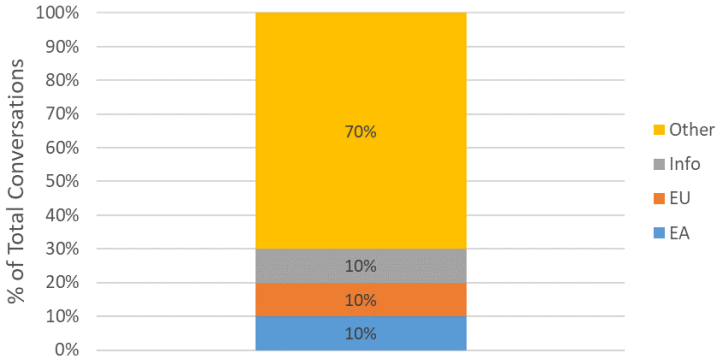
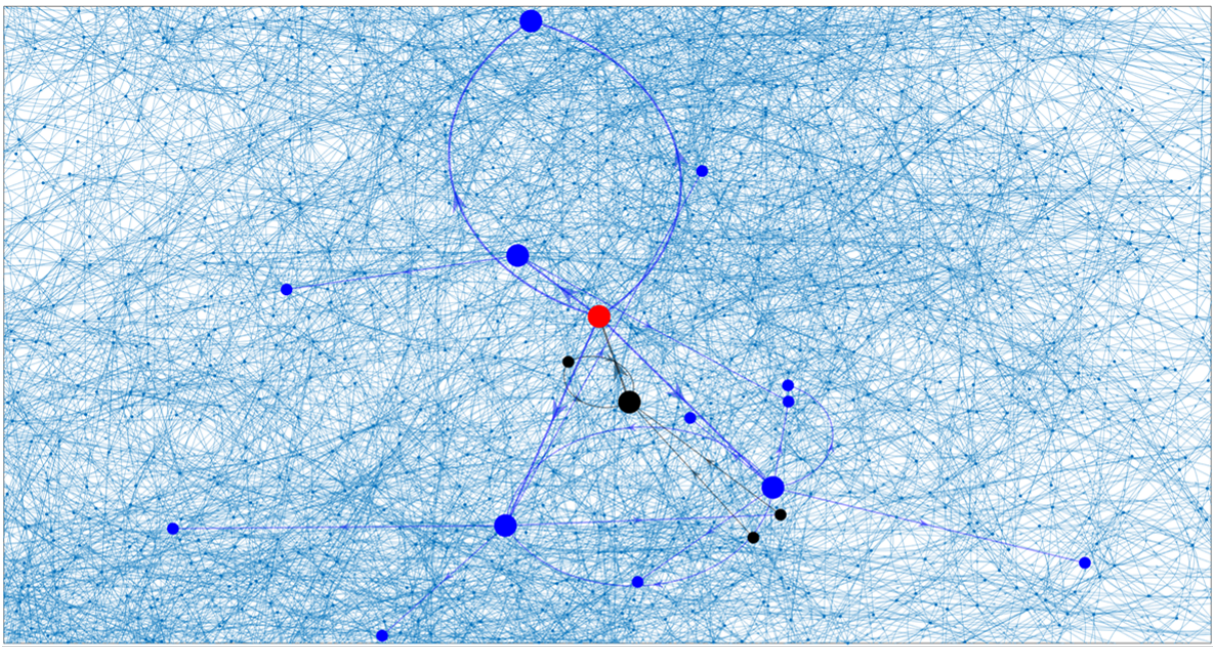


Figure 7: Distribution on conversation topics.



Agent (A)	<-->	Predecessor/ Successor (P/S)	Trust A	Trust P/S	Inj. Norms A	Inj. Norms P/S	Direction defined by	Cluster A	Cluster P/S
159	-->	792	3	5	3	3	Trust	1	1
159	-->	1654	3	3	3	4.5	Inj. Norms	1	2
159	-->	578	3	5	3	4	Trust	1	1
159	-->	578	3	5	3	4	Trust	1	1
159	-->	1160	3	5	3	3	Trust	1	1
159	<--	1390	3	4	3	3.5	Random	1	1

Figure 8: Example conversations for one agent (ID 159) on the topic of electrical appliances over the years.

Following the shocks, campaigns and conversations, the respective agent ***variables are updated***. Depending on the specification of the campaigns and the conversations, both household characteristics (e.g., the level of knowledge) and their behavioral variables (preferences) 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 (in particular, the price elasticity of residential electricity consumption from Boogen et al., 2014 in the electricity model). Regarding costs, the relative life cycle costs (investment and operating costs) of two alternatives are compared by the agents (only those agents who are likely to face a change, e.g., because the end of the lifetime has been reached). 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, compared to future expenses, such as operating costs). All these changes to the behavioral variables (preferences) 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.*** Those decisions are interlinked, that is, investments influence usage. In the investment decision stage in the electricity model the actual change of the EA stock takes place, that is, 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). In addition, however, we also consider the role of another effect that can be important in groups or networks, namely peer pressure. In our case, peer pressure can directly affect the probability that an agent buys an EEA. If within a group (in our case the family network) the probability for buying EEAs (or the preference for EEAs) is high, this can lead to an increase in an agent's EEA buying probability by partially adjusting his/her probability to that of the group. In contrast to the conversations where individual conversation partners may have an influence on my preferences (or buying probability) for EEAs, the preferences for EEAs of the whole group (average preferences here) would be taken into account when peer pressure is considered.

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.

The investment decision has an influence on the usage level. First, through changes in the stock of appliances, and second, through changes in the types of appliances (efficient or not). In addition, any change in households' efforts to reduce their electricity consumption (behavioral component) changes the consumption level. The changes in the usage level over time are represented by the previously defined production function (Eq. E1).

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 subpopulations) can be reported. Furthermore, individual agents can be tracked and traced (ex-ante or ex-post).

2.2.2 Heating ABM

Building upon the investment-usage structure of the electricity model, the heating model transfers this structure to the heating sector. Following we shortly present were the model deviates from the above-described structure.

Specification

The heat sample includes 6’365 households based on SHEDS. The definition of clusters and categories is the same in the heating model as in the electricity model, and also the (relative) distribution of households across clusters is the same. 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 m2)

- 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 17'857 kWh/a, 30% of households have a non-conventional heating system, while 20% live in a large accommodation. In terms of the age of accommodation, 25% live in an old accommodation, 15% in an old but renovated accommodation and 60% in a new accommodation.

As with the electricity model we use investment and usage related behavioral 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 behavior 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 behavioral variables (preferences) can be influenced in the simulation phase in exchanges with other actors in the conversations or through institutional campaigns, but also through price changes that affect household preferences (measured by price elasticities or relative prices or costs). 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 (20 years in the heat model). This implies that owners who own an old building can only change the building age to "old but renovated", but not to "new".

As changes in the heating system or the accommodation do not occur at regular intervals, we currently assume that approximately 10% (homegate.ch, 2017) of the renters change their accommodation every year (more often among young households and less often among older households) and owners change the heating system or renovate the building on average every 20 to 25 years (HEV Schweiz, 2021). 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. Regarding the renovation, the need for renovation also increases with the age of the windows.

The income situation of households is taken into account in the investment decision in a simplified manner. Poor households that are budget constrained (in our case, half of the poor households, which is about 30%[11]) in a period do not change their accommodation situation. Regarding the heating system,

[11] This roughly corresponds to the proportion of low-income households in Switzerland, which is 24% according to the Federal Statistical Office.

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 as a production function (Eq. H1) 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).

$$EU_h = System_h * base_{NonConv} * Size_h * \left(1 + markup_{AccomAge}\right) * Effort_h * Calib_h + (1 - System_h) * base_{Conv} * Size_h * \left(1 + markup_{AccomAge}\right) * Effort_h * Calib_h, \quad \text{(H1)}$$

where:

- EU_h is the energy usage from space heating for household h (in kWh/a).
- $System_h$ is the heating system of household h (1 = Non-conventional, 0 = Conventional).
- $base$ is the base consumption of the conventional or non-conventional heating system (in kWh/m^2/a).
- $Size_h$ is the size of the accommodation of household h (in m^2).
- $markup_{AccomAge}$ is a markup in the base consumption depending on the age of the accommodation. It is 0.8 for old buildings, 0.4 for old but renovated buildings and 0 for new buildings.
- $Effort_h$ is the effort of household h to reduce its heat energy consumption [0,1].
  $Calib_h$ is the calibration factor. It is calculated by the difference between the EU level from SHEDS and the EU function for each household h.

2.2.3 Mobility ABM

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. 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 consists of 6'395 households and 15'132 individuals (the average household size is 2.4). 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 7% have an electric car. In terms of commuting distance to work (available only for work), approximately 30% of the workers have no commuting distance (less than 1 km), 20% have a short distance of less than 10 km, 40% 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 workers 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.

As in the other models, we use behavioral variables (preferences) 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).

Usage

On the usage side, we transfer 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 (Eq. M1). The residual of this estimation is defined as preference variable that can be influenced by the model's conversation, campaign structure or prices. From the probability, we derive the actual MoT using a random variable (Eq. M2). The MoT is on an individual level and can take the values private (0) or public (1). From the individual MoT, a household-level MoT is derived, which may be mixed in addition to private or public (Eq. M3). For work and leisure time separate functions are estimated and implemented, whereas the probability function (Eq. M1) for work additionally considers the commuting distance (not available for leisure time). When literacy levels or preferences (residuals) change in the simulations, or due to random effects, individuals (and households) make changes in their MoT.

Investment

On the investment side, we use the same procedure as with the usage. We rely on an estimation function based on the SHEDS data, to identify 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 stock as dependent variable and MoT at household level (for work and leisure), norms and literacy as independent variables with further consideration of control variables and interpreting the residual as preference for private (public) transportation (Eq. M4). If in the simulations the MoT, literacy level, preferences of a household change, its stock of private (public) transport can change as well.

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 the ABM) with the probability of having an electric car as the dependent variable and norms and literacy as independent variables (Eq. M5). From the probability, we then derive the actual availability of electric cars in a household using a random variable (Eq. M6). As in the previous estimations, other control variables are considered, and the residual value is interpreted as households' preference for electric cars.

$$P(MoT_{i,h} = Public) = \frac{e^{\beta\ Cdist_{i,h} + \beta\ Norms_h + \beta\ Lit_h + \beta\ Control_{i,h}}}{1 + e^{\beta\ Cdist_{i,h} + \beta\ Norms_h + \beta\ Lit_h + \beta\ Control_{i,h}}} + \varepsilon_{i,h}, \quad \text{(M1)}$$

$$MoT_{i,h} = \begin{cases} 1, & if\ rand < P(MoT_{i,h} = Public)\ with\ rand\ [0,1], \\ 0, & otherwise. \end{cases} \quad \text{(M2)}$$

$$MoT_h = \begin{cases} 1, & if \sum_i MoT_{i,h} = 1, \\ 0, & if \sum_i MoT_{i,h} = 0, \\ 0.5, & otherwise. \end{cases} \quad \text{(M3)}$$

$$Stock_h = \beta\ MoT_h + \beta\ Norms_h + \beta\ Lit_h + \beta\ Control_h + \varepsilon_h, \quad \text{(M4)}$$

$$P\ (Ecar_h = 1) = \frac{e^{\beta\ Norms_h + \beta\ Lit_h + \beta\ Control_h}}{1 + e^{\beta\ Norms_h + \beta\ Lit_h + \beta\ Control_h}} + \varepsilon_h, \quad \text{(M5)}$$

$$Ecar_h = \begin{cases} 1, & if\ rand < P\ (Ecar_h = 1)\ with\ rand\ [0,1], \\ 0, & otherwise. \end{cases} \quad \text{(M6)}$$

Table 6: Notation of mobility model equations.

	Definition	Unit
$MoT_{i,h}$	Mode of transport for work or leisure of individual i belonging to household h	0 = private 1 = public
MoT_h	Mode of transport for work or leisure of household h	0 = private 1 = public 0.5 = mixed
$Cdist_{i,h}$	Commuting distance to work	1 = no (cdist < 1km) 2 = short (1 ≤ cdist < 10km) 3 = medium (10 ≤ cdist < 50km) 4 = long (≥ 50km)
$Norms_h$	Descriptive and injunctive norms	Descriptive (1-5) Injunctive (1-5)
$Control_h$	Variable summarizing all controls	
$rand$	Uniformly distributed random number	[0,1]
$Stock_h$	Car or Ptt stock	Number
$Ecar_h$	Electric car availability	0 = no 1 = yes
ε	Residual from SHEDS prediction. Interpreted as preference for the mode of transport, the mobility stock and electric cars	

2.3 Transfer between Workstreams 1 and 2

As is evident from the description of ABM above, both the basic structure of the model as well as its initialization and calibration depend on the work carried out in the empirical Workstream 1. Following, we will provide details on the data transfer from the SHEDS survey for the ABM initialization (Section 2.3.1) as well as on the model calibration using cantonal data (Section 2.3.2).

2.3.1 Transfer of insights from the empirical analysis to the agent-based model

The SHEDS data and the regression results of the empirical analysis are the data-driven foundation of the ABM. The model specifications differ slightly between the correlation analysis and the ABM specifications, because they have to be adjusted for the ABM-specific needs as described henceforth. As indicated in Section 2.2, the ABM uses the same five household segments as the empirical assessment to enable an easy transfer of data. In addition, further demographic household characteristics are used for specific energy areas.

In the initialization, all agents (households) are assigned values for ***energy literacy and perceived injunctive and descriptive norms***. For the assignment of energy literacy and social norms, predicted probabilities conditional on the household segments and category are used. They are obtained from ordered probit estimation models that regress energy literacy and social norms respectively on several socio-economic household characteristics. Equation (S2) describes the model for energy literacy. *X* includes the variables age, education, gender, citizenship, household income, household type and size, home ownership, spatial place of living, canton of residence and the survey year. κ is the cutoff value, $j = 0, \dots, 10$ for literacy[12] and $j = 1, \dots, 5$ for injunctive and descriptive norms respectively. The models for injunctive and descriptive norms are defined analogously. In this manner, we can account for correlations between soft incentives and other household characteristics and predict probabilities for the different values of energy literacy and social norms at the segment- and category-specific average of the socio-economic characteristics. This ensures the distribution of the two soft incentives to represent the average household of each cluster and category as good as possible. Next, sources from which the energy-related information is obtained as well as the trust in these information sources (Likert scale measurement) are allocated to agents based on distributions by household clusters taken from SHEDS. The assignment of energy literacy, social norms and information sources in the described manner is common to all ABMs. The assigned conditional distributions only differ between ABMs: In the electricity and the heat ABM the category summarizes households by household size, home ownership, and income (see Section 2.2.1). For the mobility ABM, the category describes households by household size, income, and number of workers (see Section 2.2.3). By working with descriptive statistics and conditional predicted probability distributions, we ensure sufficient heterogeneity across agents.

$$\Pr(Literacy = j|x) = \Phi\left(\kappa_j - X'\beta\right) - \Phi\left(\kappa_{j-1} - X'\beta\right), \qquad \text{(S2)}$$

For the initialization of ***energy consumption*** behavior in the three energy areas, we rely on our empirical analysis. This allows us to account for significant relations between soft incentives and the modelled behavior. The general approach is to import the distribution of energy consumption across household segments and category into the ABM. When we have identified a significant correlation with energy literacy or social norms in the previous analysis, we consider the predicted distribution of behavior conditional on the relevant soft incentive based on the estimation model. Depending on the energy area and the specific type of behavior, some adaptations have to be made to this general data transfer process in order to best map behavior in the ABM.

For the ***electricity*** ABM, data on various investment and usage behavior is extracted from SHEDS. To simulate electricity usage, the number of large electrical appliances (EA) is considered. Information about the energy label of these appliances is used to equip agents with a share of energy-efficient appliances (EEAs). To account for correlations between energy literacy, social norms, and consumption

[12] No respondent achieved the maximum number of 11 correct answers.

behavior the relevant behavioral variables (e.g., EA) are regressed on socio-economic household characteristics (X_i), energy literacy and social norms (injunctive and descriptive) analogously to our empirical analysis in Section 2.1.1. Energy literacy and social norms (T_i) are modelled in interaction with cluster indicator variables (Cl_i) in order to allow for cluster-specific correlations:

$$EA_i = \alpha + \beta X_i + \theta T_i * Cl_i + \varepsilon. \quad \text{(S3)}$$

Afterwards, we calculate predicted average values of the behavioral variable based on the model estimation. The predictions are extracted conditional on clusters as well as energy literacy and social norms in case of statistically significant correlations between the behavioral variable and the soft incentives. Otherwise, the predicted values are calculated at cluster-specific average values of the soft incentives. These values are then imported to the ABM. For the share of EEA we rely on a similar technique with a regression model for the number of EEA and calculated predicted values of EEA. These values are then divided by the number of EA to obtain the share. It is necessary to work with the predicted value of EEA here because not all respondents in SHEDS know the energy labels of their appliances. Hence, we use regression results and extrapolate to cover the entire SHEDS sample. As there could be a selection bias conditional on our variables of interest whether respondents know the energy label or not, we use a Heckman Selection Model for the estimation of EEA (Heckman, 1979). The Probit selection equation is given by $\Pr(know\ label|h_i) = \Phi(h_i\delta)$, where h_i includes socio-economic variables X_i and cluster interactions with energy literacy and social norms. The model equation for EEA is

$$EEA_i = \alpha + \beta X_i + \gamma Z_{i,e} + \theta T_i * Cl_i + u_{1i}, \quad \text{(S4)}$$

where $Z_{i,e}$ includes the accommodation age (construction date) and type. The distribution of the predicted share of EEA over cluster is then extracted for the ABM. Finally, data on the electricity usage is also imported as predicted values based on an estimation model. The values are conditioned on clusters and soft incentives (if correlations are significant). Moreover, the predicted values are calculated for electricity usage for energy services excluding heating. This is an important distinction since the reported electricity usage in SHEDS includes energy consumed for heating for households that have an electricity-based heating system. In this manner, the electricity usage in the electricity ABM only reflects behavior that should be ascribed to the electricity ABM and not for example the heat ABM. The model specification for electricity usage is given by

$$lnElecUsage_i = \alpha + \beta X_i + \gamma Z_{i,e} + \theta T_i * Cl_i + \varepsilon, \quad \text{(S5)}$$

and $Z_{i,e}$ includes accommodation age, type and size (ln), the number of rooms, bathrooms and other (i.e. garage), whether the accommodation has solar-thermal and photovoltaic panels, Minergie standard, as well as whether electricity is used for heating and warm water.

The data transfer from SHEDS to the heat and mobility ABMs follows the same approach as described for the electricity ABM with either conditional descriptive statistics or conditional predictions being used. In the case of ***heating***, only data about heating costs are available. Therefore, we have to make some assumptions about heat source-specific prices to approximate energy used for heating purposes. Since we do not observe a significant relation between soft incentives and heating costs with SHEDS data, heating usage behavior is extracted conditional on clusters, category, heating system and age of the building but not based on an estimation model. In this manner, we account for important determinants of energy consumed for heating purposes.

Some further adjustments are also necessary for the ***mobility*** ABM since mobility behavior depends on additional household characteristics. We distinguish respondents by whether they are work commuters or only travel for leisure purposes because this has an impact on the mobility behavior that has to be modelled. Additionally, we use data about the number of workers of a household and approximate the commuting distance of the respondent (in case of work outside of the home) based on information about the zip code of the home and the place of work. When we then extract investment and usage behavior from SHEDS, we can account for these influential factors. Furthermore, instead of estimation models with cluster-specific parameters for soft incentives we run separate models for each cluster. This is necessary because of the way we extract effort in this ABM. Car investments are modelled by

$$Cars_i = \alpha + \beta X_i + \gamma Z_{i,e} + \theta T_i + \varepsilon, \quad \text{(S6)}$$

where $Z_{i,e}$ includes the number of workers in the household and modes of transport for work and leisure. Investments in public transport tickets are modelled analogously. The same holds for the investment in an electric car except that a logit model estimation is performed, and modes of transport are not controlled for. A logit model estimation is also used for usage behavior (mode of transport *MoT*). The model is defined by

$$MoTwork_i = \alpha + \beta X_i + \gamma Z_{i,e} + \theta T_i + \varepsilon, \quad \text{(S7)}$$

for work and with $Z_{i,e}$ including the commuter distance. Similarly, the mode of transport for leisure is given by

$$MoTleisure_i = \alpha + \beta X_i + \theta T_i + \varepsilon. \quad \text{(S8)}$$

Finally, the ***level of effort*** exerted to reduce energy consumption is ABM-specific and depends on the data available in SHEDS for each energy area. For mobility, it is deduced from the estimation models used for consumption behavior. The residual between observed and predicted behavior is interpreted as effort. This is done for each behavior modelled in the mobility ABM. In the heat ABM, the temperature settings and venting behavior are interpreted as effort. For electricity, we rely on a SHEDS question about the intention to reduce electricity consumption (measured on a Likert scale ranging from 1 to 5).

2.3.2 Model calibration

A major uncertainty in the ABM models is the specific design of the conversations. On the one hand, the model offers many degrees of freedom regarding the design of the conversations (e.g., number of conversations or influence of the conversations). On the other hand, the literature can only help to a limited extent with regard to the specific parameters that would be required. The goal of the model calibration is therefore to find out the design of the conversations and to fix it afterwards for the scenario runs.

For the calibration we use the mobility model and run the model under historical conditions (historical price development for fuels from FSO, 2020a and for cars and electric cars from TCS, 2021 and the FSO, 2021a consumer price index). Agents respond to the historical evolution of prices by adjusting their usage and investment behavior (modeled by price elasticities and relative prices of cars and e-cars). While agents' response to prices is fixed (i.e., price elasticities remain unchanged), different conversation designs can lead to different adjustments in usage and investment behavior. To investigate this, the mobility model is run many times while the conversation parameters (i.e., the number of conversations, the definition of the direction of influence, the influence of the conversations and the networks and groups from which the conversation partners are selected) are changed step by step. The results regarding the development of the average number of cars per household from 2012 to 2019 are compared for each model run with the corresponding numbers from the Swiss Federal Statistical Office (by looking at the correlation; statistics on the average number of cars per household are calculated from FSO, 2021b and FSO, 2020b).

In order to reflect regional differences in Switzerland, the comparison between the model and the statistics is carried out at the cantonal level. However, given that very small cantons are poorly depicted in our model, as they are only represented by a few agents (due to the small number of respondents coming from these cantons in SHEDS), they are not used in the comparison (all cantons representing less than 1% of Swiss households are not considered). In the comparison, it became clear that it is important to take into account further differences in Switzerland, namely the different language regions, in the model and especially in the conversations. Accordingly, the model further distinguishes French- and German-speaking regions in Switzerland. On the one hand, the different language regions are considered in the formation of the networks (see section 2.2.1 and Figure 6) and, on the other hand, the size of the influence of the conversations can vary by language region. In the end, the calibration with the best correlation between the model and the FSO data on Swiss and cantonal level was chosen.

The final conversation design chosen, shows that in our model a few conversations per year (within the networks or with randomly selected conversation partners) can significantly influence the preferences of a household. In our model, it is not necessarily the case that many conversations influence the preferences of households in a piece-wise manner, but rather that individual conversations can already trigger changes. Additionally, in the calibration of the conversations, it was necessary to set the size of the influence of the conversations on the agents higher in French-speaking Switzerland than in German-speaking Switzerland. Thus, the conversations have a greater influence on the French-speaking agents in our model.

The correlation in the development of the average number of cars per household between 2012 and 2019 between the model and FSO data for the final conversation design is shown in Figure 9. The model represents the overall Swiss historical development of the average number of cars per household rather well with the chosen conversation design. While the correlation is rather high for most cantons, for the cantons of Zug and Basel, the correlation is zero or even negative indicating a poor fit.

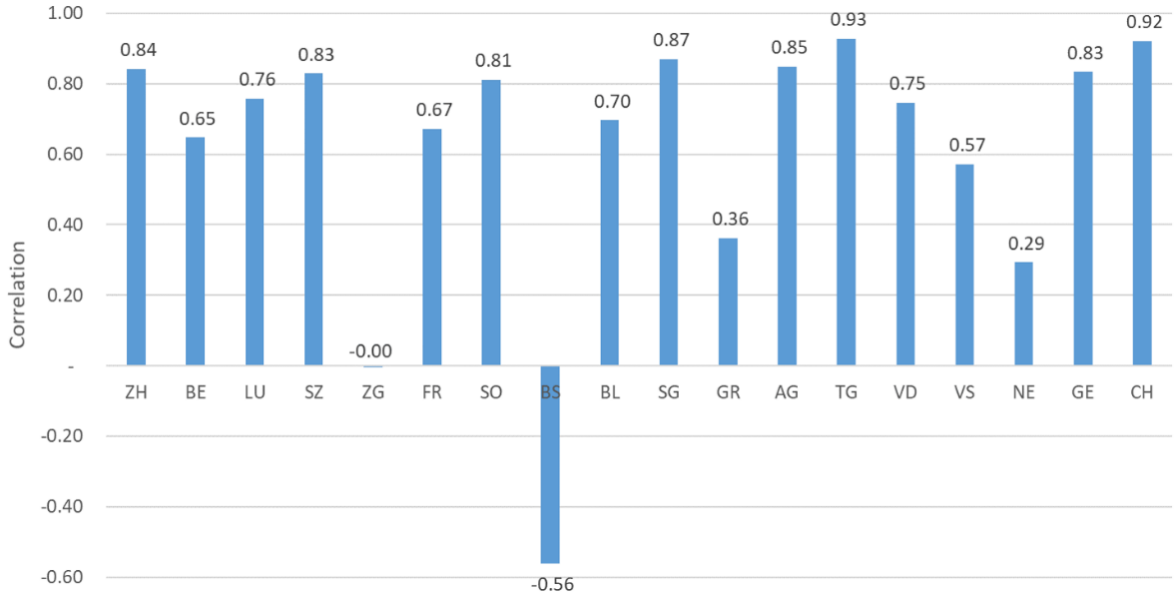


Figure 9: Correlation in the development of the average number of cars per household between 2012 and 2019 between the model and FSO data.

Figure 10 suggests that whereas we are able to represent the historical development of the number of cars at the Swiss level (Figure 10a) and also for many cantons (e.g. Zurich or Geneva, Figure 10b), the level of the average number of cars differs between our model and the statistical data. Accordingly, there seems to be a mismatch between the data from SHEDS and the data from FSO. For Basel and Zug (Figure 10c), however, not only the level but also the historical development diverges. However, as the FSO data already show, Basel and Zug are special cases: Basel has a much lower number of cars per household compared to all other cantons, and Zug has experienced a significant increase in the number of cars in recent years (approx. 10% increase).

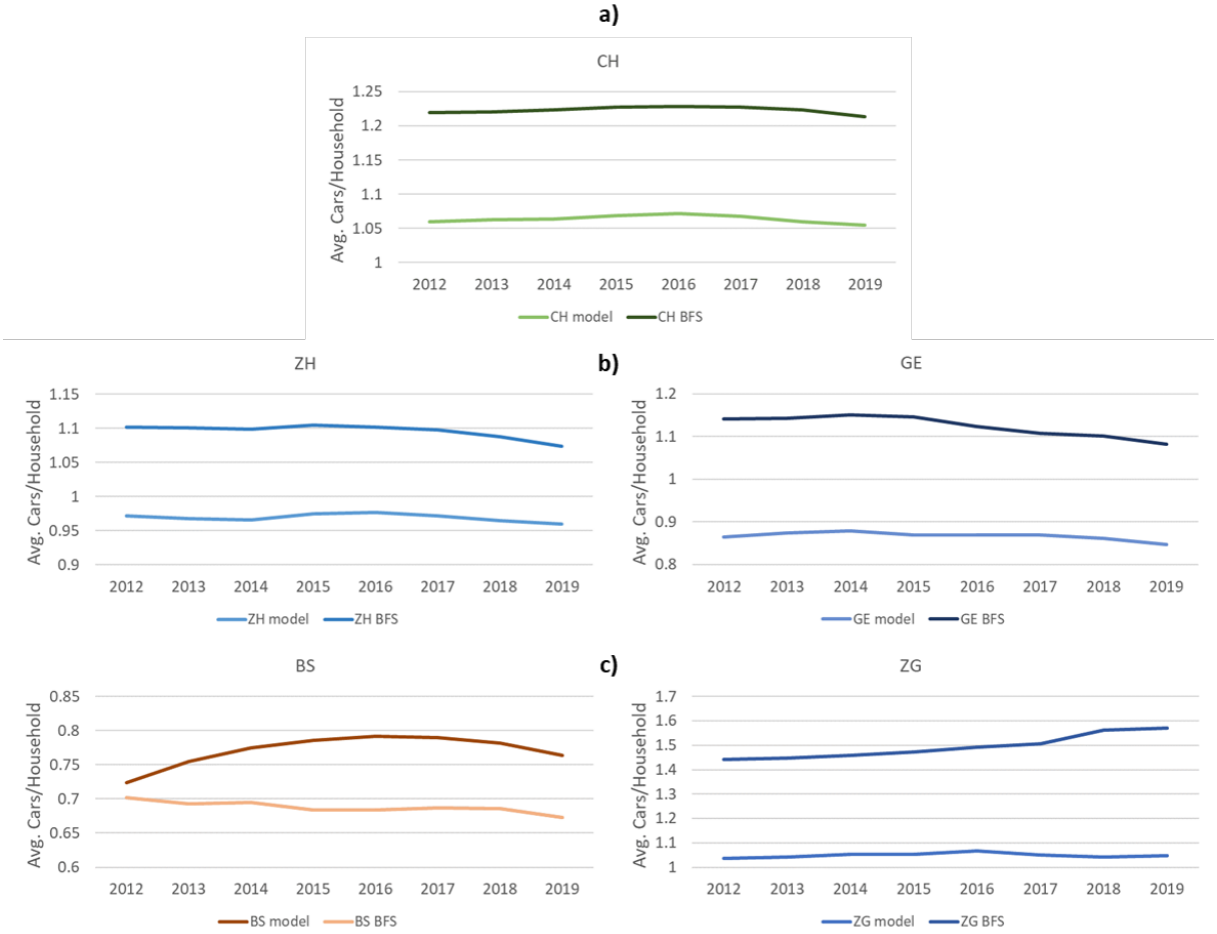


Figure 10: Historical development of average number per household according to FSO and model for selected cantons.

The selected calibration of the conversations is fixed in all scenario runs. Furthermore, the calibration of the conversations chosen using the mobility model is also applied to the other two models for electricity and heat. A separate analysis for the other two models was not possible due to a lack of detailed data.

3 Results and discussion

Following the description of the basic assessment approach above, we now present and discuss the results for the empirical analysis (see Section 4.1) and the ABM (see Section 4.2), respectively. A comprehensive summary and conclusion of the results is provided in the next section.

3.1 Workstream 1 “Empirical Analysis”

The objective of the empirical assessment is the identification of the relation between information and social norms on energy related behavior. Building upon the SHEDS dataset those relations are firstly identified on an individual level (Section 3.1.1) and afterwards validated and cross-checked using municipality data for mobility (Section 3.1.2)

3.1.1 Individual level analysis

The results of our empirical analysis of the SHEDS data with data from all five years are summarized in Table 7. Table 8 and Table 9 report estimates for literacy and social norms for the main model specifications analyzed per behavior. Full regression tables for these model specifications are provided in Appendix 10.4. Households with a high level of energy literacy are on average more likely to have made energy-saving and environmentally friendly investment choices in all three investigated areas of household energy demand compared to households with little energy-related knowledge. There is also evidence for a positive relation between a household’s perception of social norms and such behavior in the areas of mobility and electricity. For heating investments, we find no significant correlation with social norms.

Looking at usage behavior, we find both soft measures to be important. Literacy is significantly related to all types of analyzed mobility behavior. The same holds for social norms with the exception of flying behavior. Here, social norms are positively correlated with the number of flights, whereas literacy has a negative correlation. Contrary to the area of mobility, social norms are more relevant for electricity usage behavior than literacy. Although energy literacy is correlated with a lower and less frequent use of electric appliances, social norms are significantly related to electricity usage and energy-saving handling of electric devices. Survey respondents, who perceive peer pressure (especially from friends) to behave environmentally friendly, report smaller electricity bills and lower electricity usage than respondents with no perception of such social norms. We find energy literacy to have a concave correlation with electricity usage.

Electricity

In the area of electricity, our analysis suggests that social norms and energy literacy are both relevant for energy consumption but there are some differences across types of behavior. When it comes to investment decisions, social norms, in particular injunctive norms, are a consistent incentive. There are statistically significant correlations with all analyzed investment choices, and they imply a positive relation to energy-saving and environmentally friendly behavior. In the case of literacy, we also find significant relations for all investments. However, the direction is opposing for investments in energy efficient appliances. Although we find people with a high literacy to be more likely to know the energy efficiency label of their appliances, the correlation between literacy and the label is negative. This negative correlation could be due to the infrequent replacement of the appliances and to the data

representing a moment in time. Although some people have the necessary knowledge to invest in energy efficiency, they might not have faced such an investment decision recently.

Table 7: Summary of estimation results of SHEDS

	Investment Choices					Usage Choices				
	Behavior	**Variable**	**Lit**	**Inj**	**Desc**	**Behavior**	**Variable**	**Lit**	**Inj**	**Desc**
Mobility	Public transport subscription	GA	+	+		Mode of transport: Car (vs. public transport/soft mobility)	Work	-	-	
		HTA	+				Leisure	-	-	
		RA	+ (nl)				Grocery		-	
	Number of vehicles	Cars	-	-	+	Distance by car	Self-assessed	-	-	
		Motorbike		-			Odometer			+
		Bike	+	+	-	Flying (short/long distance)	Flight costs	-		
		E-bike	+	+			Number of flights	-	+	+
	Car engine	Electric	+		-					
Heat	Non-conventional (vs. conventional) type of system	Heating	+			Heating costs	Heating costs			
						Average room temperature	Temperature	-	-	-
						Energy-saving heating behavior	Index	+	+	+
						Energy saving venting behavior	Venting	+		
		Warm water	+			Frequency of showers/baths	Shower/Baths			
						Energy saving shower behavior	Turn off shower	+	+	+
Electricity	Electrical appliances	Number	-	-		Switch-off behavior	Switch off		+	+
	Energy label of appliances	Label	-	+	+	Usage of electronic appliances	Frequency (per week)	-		
		Know label	+	+	+		Duration (h/day)	-	-	-
	Tariff choice	Tariff change	+	+	-	Usage and costs of electricity	Costs		-	
							Usage			

Note: Columns “Lit”, “Inj”, and “Desc” summarize the direction of significant correlations between behavior and the soft incentives energy literacy, injunctive norms, and descriptive norms respectively. (nl) implies a non-linear relation.

Table 8: Summary of estimation results - investment choices

	Investment Choices					
	Behavior	**Variable**	**Estimation**	**Lit**	**Inj**	**Desc**
Mobility	Public transport subscription	GA	Poisson	0.07***	0.17***	-0.1***
		HTA	Poisson	0.02***		
		RA	Poisson	0.09**, -0.01* (nl)		
	Number of vehicles	Cars	Poisson	-0.03***	-0.06***	0.04***
		Motorbike	Poisson		-0.11***	0.06*
		Bike	Poisson	0.04***	0.06***	-0.05***
		E-bike	Poisson / Probit	0.06*** / 0.05***	. / 0.05**	
	Car engine	Electric	Probit	0.05**		
Heat	Non-conventional (vs. conventional) type of system	Heating	Probit	0.02*		
		Warm water	Probit	0.03**		
Electricity	Electrical appliances	Number	Poisson	-0.01***	-0.01***	0.01*
	Energy label of appliances	Label (A+++ to C or worse) – Tv	Ordered Probit	0.04***		-0.08***
		Label (A+++ to C or worse) – Fridge		0.03**		
		Label (A+++ to C or worse) – Wash		0.03**		
		Label (A+++ to C or worse) – Dish				
		Know label – Tv	Probit	0.03***	0.06***	0.03*
		Know label – Fridge		0.05***	0.08***	
		Know label – Wash		0.04***	0.05**	0.05**
		Know label – Dish		0.04***	0.05***	
	Tariff choice	Tariff change	Probit	0.09***	0.13***	-0.09***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns “Lit”, “Inj” and “Desc” show point estimates of energy literacy, injunctive norms and descriptive norms, respectively. Estimates reported for the main model specification used for each behavior. The column “Estimation” describes the type of estimation model. All models include socio-demographic and household-level control variables: Age, gender, education, Swiss citizenship, household size and type, home ownership, place of living and canton. Additional controls are model-specific. Heat investment models also control for accommodation age, Minergie standard, renovations, accommodation type.

Table 9: Summary of estimation results - usage choices

	Usage Choices					
	Behavior	**Variable**	**Model**	**Lit**	**Inj**	**Desc**
Mobility	Mode of transport: Car (vs. public transport/soft mobility)	Work	Multinomial Logit	-0.07***	-0.16***	0.09**
		Leisure	Multinomial Logit	-0.09***	-0.22***	0.12***
		Grocery	Multinomial Logit		-0.21***	
	Distance by car	Self-assessed	Ordered Probit	-0.02**	-0.05***	0.05***
		Odometer	OLS		-0.03**	0.04**
	Flying (short/long distance)	Flight costs	OLS	-0.04***		
		Number of flights	Negative binomial	-0.03***		0.03*
Heat	Heating costs	Heating costs	OLS (Log-Lin)			
	Average room temperature	Temperature	OLS	-0.02***	-0.08***	
	Energy-saving heating behavior	Index	Poisson	0.01***	0.02***	
	Energy saving venting behavior	Venting	Ordered Probit	0.06***		
	Frequency of showers/baths	Shower/Baths	OLS (Log-Lin)			
	Energy saving shower behavior	Turn off shower	Ordered Probit	0.01**	0.06***	
Electricity	Switch-off behavior	Switch off (often to almost never)	OLS		-0.08***	
	Usage of electronic appliances	Frequency (per week)	OLS (Log-Lin)	-0.01**	-0.02*	
		Duration (h/day)	OLS (Log-Lin)	-0.02**	-0.04***	
	Usage and costs of electricity	Costs	OLS (Log-Lin)		-0.02*	
		Usage	OLS (Log-Lin)			

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns “Lit”, “Inj” and “Desc” show point estimates of energy literacy, injunctive norms, and descriptive norms, respectively. Estimates reported for the main model specification used for each behavior. The column “Estimation” describes the type of estimation model. All models include socio-demographic and household-level control variables: Age, gender, education, Swiss citizenship, household size and type, home ownership, place of living and canton. Additional controls are model-specific. Heat usage models include control variables for accommodation age, type and size (log), Minergie standard, renovations, number of rooms, bathrooms and other (i.e. garage), heating and warm water systems. Electricity usage models control for accommodation age, type and size (log), number of rooms, bathrooms and other (i.e., garage), solar thermal panels, photovoltaic panels, electric heating and warm water and Minergie standard.

Heat

For space heating and warm water, we find that only energy literacy is related to investment choices. It increases the probability of having a heating and warm water system that is based on non-conventional sources (i.e., heat pump, district heating, solar, wood) instead of a conventional one (i.e., oil, gas, electricity) by 0.005. Regarding usage, soft incentives are significantly correlated with energy-saving heating behavior, such as having a lower average room temperature, energy-saving heating system settings and venting behavior, as well as water-saving shower routines (see Table 9). However, we do not find this relation represented in lower reported heating costs (based on actual consumption) for households with high levels of energy literacy or a strong responsiveness to social norms.

Mobility

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. Both incentives are related to fewer cars, as well as more bikes and e-bikes in a household. Furthermore, literacy is positively correlated with public transport tickets in the household and the availability of an electric car. With usage behavior, a high level of literacy and social norms relates to a lower probability of the car chosen as the preferred mode of transport for work, leisure, and grocery shopping, which also reflects in a negative correlation between the incentives and the stated distance driven by car. Finally, literacy has a positive relation with reduced flying behavior, whereas social norms are related to more flying.

Norms

Looking more closely at social norms, our analysis suggests that household energy demand is more strongly related to injunctive norms than descriptive norms. Particularly for usage decisions in the areas of heating and electricity, we only find a significant relation between behavior and injunctive norms but not with descriptive norms. Also, coefficients for injunctive norms tend to outweigh descriptive norms (see Table 8 and Table 9). For example, an increase of injunctive norms by one unit is related to 0.06 fewer cars whereas an increase in descriptive norms is related to 0.04 more cars on average. The probability of using a car for leisure also decreases by 0.05 with injunctive norms but increases by 0.02 with descriptive norms on average. In many other cases as well, such as other mobility investments and usage behavior or the choice of the electricity tariff, we find the correlation between social norms and the behavior to go in the opposite direction with descriptive norms compared to injunctive norms. A possible explanation for this observation could lie in the measurement of social norms within SHEDS. Descriptive norms are measured by the perceived extent of environmentally friendly behavior of peers. The literature on the effects of descriptive norms on pro-environmental behavior describes a negative “boomerang effect” for people who behave above the norm (Schultz et al., 2007). In the present analysis, respondents who behave environmentally friendly could assess their peers’ behavior as less environmentally friendly and vice versa, which could lead to the observed negative correlation between norm and pro-environmental behavior.

Heterogeneity

Across different household segments, there is substantial and important variation with regard to correlations between the soft incentives and energy consumption behavior. In many instances, the results for the full sample are not representative for all segments in that some segments either show no significant correlation in contrast to the full sample or show a significant correlation even though the full sample does not. Table 10 summarizes estimation results for the behavioral variables that are transferred to the ABMs and based on the ABM model specifications (see Section 2.3.1) and shows, which clusters react to which incentive. The full estimation results are reported in Table 11 and Appendix 10.2. Middle-aged households in urban areas in Cluster 3, for example, are more likely to have an electrical car if they have a strong perception of injunctive norms. With such a strong perception, they are 37 percentage points more likely to have made such an investment, whereas there is no relation to the level of literacy in this cluster.[13] The full sample results in contrast indicate a positive correlation between the investment in an electric car and energy literacy. At the cluster level, we find this correlation for the senior segment.[14] A clear pattern of consistent susceptibilities of clusters to a specific soft incentive is not determinable.

Table 10: Summary of estimation results used for the ABMs at cluster level

	Investment Choices				Usage Choices			
	Behavior	**Lit**	**Inj**	**Desc**	**Behavior**	**Lit**	**Inj**	**Desc**
Mobility	Number of public transport tickets	(+) 2, 4	(+) 2, 3, 4	(-) 2, 3, 4	Private MoT: work	(-) 1, 2, 3, 4	(-) 1, 3, 4, 5	(+) 4, 5
	Number of cars	(-) 1, 2, 3	(-) 1, 4	(-) 2; (+) 3	Private MoT: leisure	(-) 1, 2, 3, 4	(-) all	(+) 3, 4, 5
	Electric car	(+) 5	(+) 3	(+) 3				
Heat	Non-conventional heating system	(+) 2,3						
Electricity	Electrical appliances	(-) 1, 3, 4	(-) 1		Electricity usage	*(-) 2*	(-) 1	
	Number of EEA	(-) all	(+) 2	(+) 1, 3				
	Know label	(+) all	(+) 3, 4	(+) 2				

Note: Columns “Lit”, “Inj”, and “Desc” summarize the direction of significant correlations between behavior and the soft incentives energy literacy, injunctive norms, and descriptive norms respectively, as well as for which cluster the correlation is found. Clusters: 1 is the cluster of young households in urban areas, 2 describes young households in rural areas, 3 and 4 are mid-age households in urban and rural areas respectively, and 5 is the cluster of senior households (see Table 3 for the cluster description).

[13] The number of people with an electric car is relatively low in the sample. Thus, the sample size for the cluster-specific estimation models is also restricted. The strong correlation observed here should be interpreted with caution.

[14] An estimation model with the full sample but cluster-specific parameters for the correlations with soft incentives indicate a positive correlation for other clusters than Cluster 5 as well. As the results imported to the ABM rely on the cluster-specific estimation model due to methodological reasons, we report this result here instead.

In this sense, our empirical analysis highlights the relevance of the different household types, as the strength of the correlation between soft incentives and energy consumption varies across segments. As a further illustration, Table 11 presents estimation results of a model for the number of cars for the full sample and the five clusters.[15] Energy literacy as well as social norms are significantly correlated with the number of cars in a household. However, the estimation results show that the magnitude of the relation differs between the soft incentives, and one outweighs the other in each model. Households in Cluster 1 (young people living in urban areas) are estimated to have fewer cars when they have a high level of literacy and a strong perception of injunctive norms compared to households in the same cluster who do not have such strong values. The results imply a reduction of the number of cars by -0.16 between low and high levels of literacy and a reduction of -0.13 between no perception and a high perception of injunctive norms. In this example, Cluster 1 is the only household group with a significant relation for these two types of soft incentives. For young people living in rural areas (Cluster 2) literacy relates to -0.23 and descriptive norms to -0.17 cars between low and high levels of the two soft incentives. For Cluster 3 (mid-age urban households), we find a significant negative correlation between literacy and the number of cars, whereas with descriptive norms we find the previously described opposite correlation. A particularly strong correlation between injunctive norms and the number of cars but no correlation between literacy and cars is observed in Cluster 4 (mid-age rural households). Lastly, for senior households (Cluster 5) we find no significant correlation between soft incentives and the number of cars in the household. Such differences across households are observable for investment and usage choices and for all three areas of energy demand (see Table 10). Further regression estimation results used as an input in the ABMs can be found in Appendix 10.2.10.2. Note that the full sample results in Appendix 10.210.2 can slightly deviate from the results presented in Table 8 and Table 9 because of the methodological adjustments necessary for the transfer to the ABMs (see Section 2.3.1, Table 10).

Table 11: Estimation results of the number of cars for the full sample and the five clusters.

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	-0.02***	-0.02**	-0.02**	-0.02**	-0.01	-0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Injunctive norms	-0.02**	-0.03**	0.01	-0.01	-0.09***	0.01
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Descriptive norms	0.01	0.01	-0.04*	0.04**	0.02	0.03
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Constant	0.03	0.01	0.54***	-0.00	-0.32	1.11***
	(0.09)	(0.21)	(0.20)	(0.22)	(0.29)	(0.36)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Socio-demographics	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
MoT controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6216	1569	1199	1120	1475	853
R squared	0.51	0.51	0.54	0.53	0.42	0.47

Note: Standard errors in parenthesis. + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001. OLS estimation.

[15] The same estimation model was used for the transfer of the results to the Mobility ABM. Because of the methodology used for this transfer, we do an OLS estimation instead of estimating a Poisson model.

Price elasticity

In addition to the analysis of the direct relation between soft incentives and energy consumption, we have also investigated the relevance of soft measures for price elasticities in the area of electricity. Using data provided by ElCom (see Section 2.1.1) we find a price elasticity of -0.84. Over our five different household segments, there is no significant variation of the elasticity. Although our result is more elastic than some estimates in the literature, it comes close to recent evidence by Boogen et al. (2021), who find a short-run price elasticity of -0.7 in Switzerland.

Moreover, we find soft measures to affect the price elasticity. Energy literacy has a significant relation to price elasticity. The elasticity is estimated to be more elastic with a high level of literacy. The elasticity ranges from -0.82 to -0.88 between low and high literacy levels. The more elastic electricity demand of highly energy literate households indicates that their knowledge better equips them to adapt their behavior to save electricity compared to households with a low literacy. In contrast, we did not find social norms to affect the price elasticity in our analysis.

Whether these results also apply to households with other electricity tariffs than the standard one cannot be answered with this analysis. What a regression analysis of the full SHEDS sample shows is that households with a standard electricity mix have on average no statistically different electricity consumption than households with a more environmentally friendly, pricier mix.

Discrete choice experiment

The analysis of the home relocation discrete choice experiment suggests 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 11, 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 in line with our expectation.

However, the full sample results overlook the extent of the 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 an increase of the 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 and 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 housing size and are more likely to downsize the larger their current per person living space is. The information treatment also reduces the choice probability of an increase of the living space. The effect is stronger the less living space is currently available per person. Finally, senior households can be positively influenced through social norms to reduce the choice probability of an increase of the housing size.

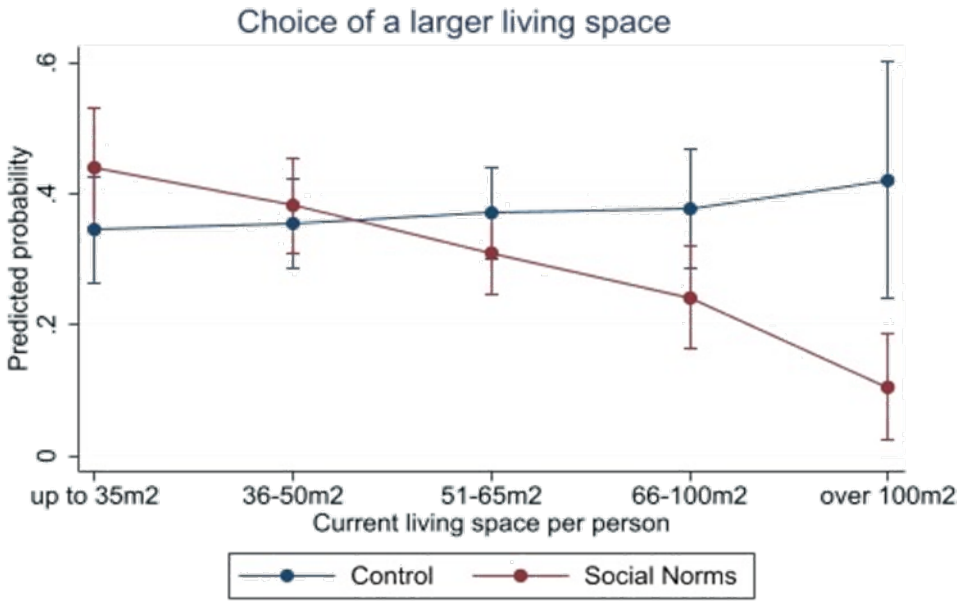


Figure 11: Predicted choice probability for a larger than currently inhabited living space for the full sample at different levels of currently inhabited space per person.

3.1.2 Municipal level analysis

Regarding the empirical analysis at the municipal level, Table 8, 9 and 10, provide the descriptive statistics for the socio-demographic and economic variables, proxies for social norms and information, and the mobility behavior variables, respectively.

The statistics show that on average people between the ages of 20 and 64 years are the majority (i.e., 60.6%) in Swiss municipalities, with an average household size of 2.3 (Table 12). For the assessment of the voting behavior, we relied on the three most recent environmental ballots that are related to energy issues. We mostly use the Energy Act (6120) as the votes were favorable (i.e., 58%). As robustness check, alternatively, we consider the other two initiatives that did not get the majority during the vote: Nuclear Withdrawal (6080) with 45.2% and the green economy (6050) with 45.5 %. Furthermore, we use the share of green and green/left parties in the national vote 2015 as proxies. As is evident from the statistics, there is a large variability across municipalities (Table 13). For the environmental ballots the range between lowest and highest shares is about 30 percentage points, while for the national vote the differences are even larger.

Regarding the green business indicators, we have decided to use the stock instead of the availability for the LED bulb, as this green product is available in almost all the Migros shops (98%). We have also considered the availability of some organic products: organic eggs, and three types of organic breads (Ciabatta, Autrefois and Twister). Similar to the LED bulb availability, we have chosen not to use information on organic eggs, as this organic product is available in almost all the Migros shops (95%). Among the three organic breads, “Autrefois” has a moderate availability (58.3%), while “Ciabatta” has the lowest (42.9%) and the “Twister” the highest availability (80.7%). Therefore, we primarily use organic bread “Autrefois” and the other two organic breads are considered for the robustness check.

In Table 14, the distribution of public transport cards indicates that the HTA is five times higher than the GA, given the high price difference between the two cards. In addition, the distribution with respect to the car efficiency dictates that the worst label (G) has the highest percentage (47.2%), while the best label (A) represents only 3.5% of the cars.

Table 12: Descriptive statistics for the municipal data: Socio-demographic and economic variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Log population	2570	7.885	1.388	2.639	12.906
Log density	2570	5.156	1.533	.046	9.433
Age 0-19	2570	.204	.032	0	.316
Age 20-64	2570	.606	.031	.214	.778
Age 65+	2570	.189	.042	.08	.643
Household number per population	2570	.426	.036	.302	.786
Household size	2570	2.33	.198	1.27	3.160
Job per population	2569	.458	.283	.072	4.342
Log average taxable income (CHF)	2535	11.139	.264	10.229	13.662

Table 13: Descriptive statistics for the municipal data: Social norms and information variables.[16]

Variable	Obs	Mean	Std. Dev.	Min	Max
Voting behavior					
Vote for the Energy Act (6120) in %	2570	.580	.075	.44	.74
Vote for the Nuclear Withdrawal (6080) in %	2570	.452	.062	.32	.60
Vote for the green economy (6050) in %	2570	.355	.064	.22	.52
Vote for the green party, national election, 2015 in %	2534	.094	.053	0	.401
Vote for the green/left parties, national election, 2015 in %	2534	.250	.104	0	.611
Green business					
LED bulb P (availability)	2570	.986	.086	0	1
LED bulb P (stock)	2570	5.424	2.268	0	44
Organic egg (availability)	2570	.950	.164	0	1
Organic bread Ciabatta (availability)	2570	.429	.354	0	1
Organic bread Autrefois (availability)	2570	.583	.364	0	1
Organic bread Twister (availability)	2570	.807	.277	0	1

[16] Given that LED bulbs are more cost efficient than alternatives and thus a perfectly informed individual can be expected to choose LEDs, we take the LED bulb variables as a proxy for information, whereas all other variables are seen as proxies for social norms.

Table 14: Descriptive statistics for the municipal data: Mobility behavior.

Variable	Obs	Mean	Std. Dev.	Min	Max
Private and public transport (per 1000 inhabitants)					
Total car	2570	604.838	104.677	44.006	1875.536
Abonnement General (GA)	2535	30.5	29.118	.119	228.008
Half fare card (HTA)	2569	173.115	130.014	.254	776.942
Car Efficiency (as a share of total car)					
Label A	2570	.035	.016	0	.163
Label B	2570	.026	.011	0	.084
Label C	2570	.055	.02	0	.461
Label D	2570	.068	.018	0	.185
Label E	2570	.093	.022	0	.2
Label F	2570	.154	.029	.058	.26
Label G	2570	.472	.074	.17	.732

Using the municipal data described above, we have conducted an econometric analysis for the full sample and by cluster. The results for the full sample estimation are summarized in Table 15. 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 correlation with buying public transport cards and the share of clean electric vehicles. On the contrary, information has a negative and significant correlation with 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 correlation with the number of cars in the municipality. While their correlations with public transport cards and clean electric vehicles are positive and significant, the green business proxy has no significant correlations. We also find the same contradictory correlations 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 15: Summary results for the full sample[17]

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

Note: Cases where the results at the municipal level differ qualitatively from those at the individual level are set in boldface. Results for the shares of dirty hybrid, Label A and G are not available at the individual level, due to this data not being available in SHEDS.

17

Table 16 summarizes the results for the cluster estimation. We find that Information (Inf) and Social Norms (SN) have different correlations with the decisions across clusters. For example, information only significantly and positively correlates with public transport cards for cluster 1 (Young in the city), while social norms have negative and significant correlations with the public transport card GA for cluster 2 (Young in the rural area). Regarding the private transport decision, information has a significant and negative correlation only for Cluster 4 (Middle age in rural areas) while social norms have the same correlation for Cluster 2 and Cluster 3 (Middle age in the city). Overall, our results indicate a significant heterogeneity across clusters.

Table 16: Summary results for the cluster estimation.

Cluster	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(-)

Results summary for Workstream 1

The empirical analysis in this project has provided a detailed picture of options for reducing household energy demand that covers the domains of electricity, heat, and mobility, investment and usage aspects in each domain, and monetary incentives as well as soft instruments. Apart from the detailed results, this analysis provides a few key insights:

1. Soft instruments have potential for reducing household energy demand, the effects may be small (e.g., energy literacy for several clusters) but these instruments show a significant negative correlation with behaviors that increase energy demand for many clusters and domains of energy use.
2. The correlations between soft instruments and energy-related behavior differ strongly between instruments (information, injunctive or descriptive norms), domains of energy use, and the five considered household segments (clusters).
3. This implies that targeting the use of soft instruments to particular household segments might be beneficial.
4. The very simple approach to household segmentation (based on age and place of residence) has proven to be highly effective.

These key insights are based on the analysis of the SHEDS data. However, the complementary approaches (analysis of municipal data and choice experiment) provide similar general conclusion, if the differences in data coverage and methods are taken into account. Thus, we think the above key insights are likely to be fairly robust.

3.2 Workstream 2 “Agent-Based modelling”

The objective of the ABM is to translate the empirical findings on household behavior into simulations of development pathways for a set of different policy interventions given the underlying decision representation. To this end a scenario outlet needs to be defined and simulated with the ABM. Following we will present the underlying scenario assumption (Section 3.2.1) and the resulting model findings (Section 3.2.2).

3.2.1 Scenario description

To investigate the interplay between monetary and soft policies as well as the feedback effects from social norms and information diffusion across households the scenario framework needs to capture a range of measures for the investigated three sectors. In an exchange with the SFOE and EnergieSchweiz the following illustrative interventions were specified:

- Tax on CO_2-intensive goods
- Subsidies for clean goods
- Campaigns:
    - Information campaign about the main objectives of the new CO_2 law[18]
    - Campaign with an "injunctive norm"
        - "It is socially accepted that future mobility / heating must become green to save the climate. We have the technology to do it".
    - Campaign with a "descriptive norm“
        - "It has been observed that more and more people are changing their transportation / heating systems to environmentally friendly options".

The implementation of these scenarios in the individual models is shown in Table 17. A tax on CO_2-intensive goods is implemented by a tax on fossil fuels of 200 CHF/t CO_2 in the ABM on heating and mobility. In the subsidization of clean goods, efficient appliances are subsidized in the electricity ABM, and non-conventional heating systems and efficiency improvements (more precisely renovation or renewal of the windows) are subsidized in the heating ABM. In the mobility ABM, electric vehicles are subsidized. In each case, two levels of subsidy are considered, one that makes the clean good equal in price and one that makes the clean good cheaper.

Information and norm-related campaigns are implemented in ABM in two ways. On the one hand, such campaigns can influence the diffusion of information among households (by increasing the likelihood that a particular topic, such as electric appliances, heating system, or mode of transport, will be raised in a conversation). On the other hand, they can directly influence literacy of households or use norms as a channel to transport a message in order to address a specific target variable (e.g., energy efficient appliances, heating system or mode of transport). With regard to the timing of the soft measures, a single-period measure as well as a multi-period measure is considered.

[18] In the referendum of June 13, 2021, the revised CO2 Act was rejected. However, the modeled campaign was already defined beforehand and not changed afterwards.

Table 17: Scenario implementation by model.

Scenario	Electricity ABM	Heating ABM	Mobility ABM
Tax	-	**CO_2 tax** ($200 CHF/t CO_2$)	**CO_2 tax** ($200 CHF/t CO_2$)
Subsidy	**Efficient appliances** (15% and 30% price reduction)	**Non-conventional system** (30% and 40% price reduction) **Renovation** (20% and 40% cost reduction)	**Electric vehicles** (15% and 30% price reduction)
Information campaign	• Campaign for one (= period 4) and more periods (= periods 3 to 5) • Effect on the **diffusion of information** (increase likelihood to talk about EA, Heating System, MoT) • Effect on **literacy** or use of **norms** as a **channel** (targeting EEA, Heating System and MoT)		
Injunctive norm campaign			
Descriptive norm campaign			

Combination of hard and soft measures

In the first step, all households (agents) are subject to the same individual measures (i.e., there is no policy differentiation). Afterwards, we also consider a combination of measures. More specifically, in the electricity model we consider a combination of a subsidy for energy-efficient appliances and a one-year descriptive norms campaign. In the heating and mobility models, we combine a CO_2-tax and a one-year descriptive norms campaign.

Targeting of soft measures

As one of the main advantages of the ABM is the detailed representation of heterogeneous households we subsequently consider targeting of measures to individual groups. This 'tailoring' is limited to soft measures.

With regard to the targeted measures, a three-step procedure is applied. First, a measure addresses all households in order to analyze which groups or subgroups react to the measure and how. Groups or subgroups that can be analyzed in this regard are specified based on observable socioeconomic and demographic characteristics (so that policymakers or institutions can identify and target these groups). In the models, groups or subgroups can thus be defined based on clusters, categories, or other characteristics derived from SHEDS. Second, based on the results of the first step, the measure is then targeted to specific groups that respond to a measure. In the analysis conducted here, however, we focus only on a targeting on clusters. Finally, the measure can be fine-tuned.

3.2.2 Scenario results

In this section, we show the results of the scenario runs. First, we looked at the results of the electricity ABM, followed by the results of the heating and mobility ABMs. Finally, we summarize the main findings. Please note that the results and figures presented here do not represent a prediction of future developments. Rather, they allow a comparison across scenarios, e.g., the direction of the impact of a monetary measure or a campaign.

Electricity ABM

For the electricity ABM we simulate a time frame of 10 years. In presenting the results, we focus on the average share of energy efficient appliances (EEA Share) and compare the base case with the respective scenarios. In the base case, prices are constant, and no campaigns take place. A look at the black dotted line in Figure 12 (left panel) shows that in the base case, the share of energy-efficient appliances increases over time. While the EEA share is already rather high in the first period, agents' exchange and learning in the conversations leads to an increase in preferences for energy-efficient appliances and thus to a further increase in the EEA share over time.

Subsidy on energy-efficient appliances

The introduction of a subsidy for energy-efficient appliances, which makes efficient and non-efficient appliances equal in price (orange line in Figure 12left panel), leads to a further increase in the EEA share. On the one hand, agents (facing a change) make a relative costs comparison. A subsidy consequently makes EEAs more attractive from a cost perspective and thereby tends to increase the preferences of the agents for this product. On the other hand, as price effects in our models (measured by price elasticities or relative costs) influence household preferences, the cost comparison also results in some agents entering conversations with other agents with changed preferences and thus other agents can be (further) influenced. Interestingly, a higher subsidy (yellow line in Figure 12 left panel) that makes efficient appliances cheaper than non-efficient appliances is limited in its additional benefits. The reason is that the EEA share is already at 100 percent for many agents, so they cannot increase their EEA share further even with additional subsidies.

In the right panel of Figure 12, we compare the base case with the high subsidy for EEAs (which leads to a 30% cost reduction) at the cluster level. The base case shows that especially the young people living in the city (cluster 1) have a high share of energy-efficient appliances, whereas the middle-aged people living in the agglomeration and in the countryside (cluster 4) as well as the older people (regardless of location; cluster 5) have a slightly lower share of EEAs. However, the base case shows that especially cluster 4 has a strong increase in EEA share over time. Subsidizing EEAs leads to a significant increase in EEAs for all clusters compared to the base case. However, the effect of the subsidy is the same for all clusters, as we do not account for possible cluster-specific differences in the response of actors to prices

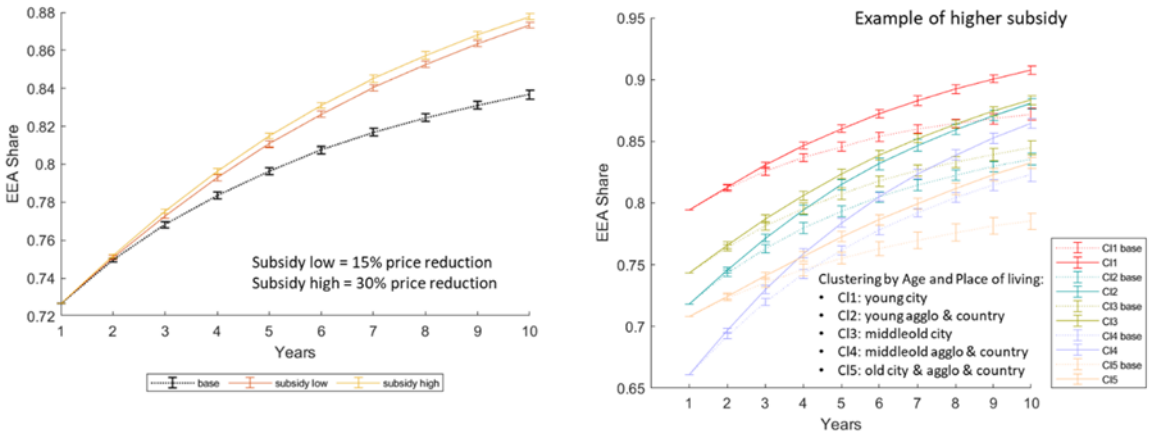


Figure 12: Subsidy for energy-efficient appliances in the electricity ABM.

Diffusion of information campaigns

Next, we simulate a campaign that increases the probability that a topic (i.e., electric appliances) is discussed by the agents in the conversations. Here, the increase in probability depends on the descriptive (desc id) or injunctive (inj id) norms of the two agents talking to each other, and the higher the overall level of norms, the more likely it is that the agents talk about electric appliances. Additionally, we consider a case where the agents exchange information more frequently (lit id), thus increasing the frequency of learning (depending on the literacy level of the two agents). The development of the EEA share by campaign and in comparison, to the base case is shown in Figure 13. However, both the average EEA share across all households (left panel) and the cluster-specific development (right panel) show no significant change in the EEA share due to information diffusion.

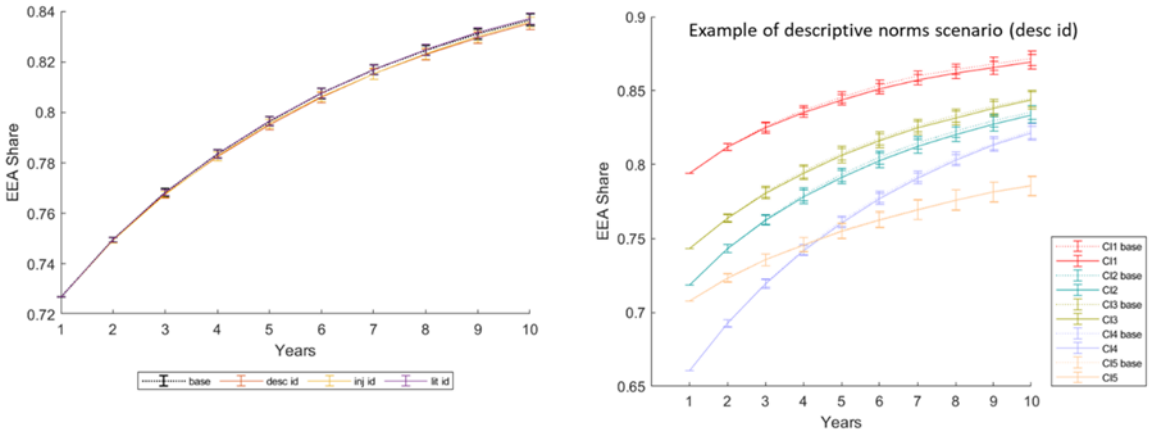


Figure 13: Diffusion of information in the electricity ABM.

Literacy campaign

Similarly, a literacy campaign that does not affect literacy levels through conversational learning but changes literacy levels directly through information provided by an institution does not lead to a change in EEA share. While the literacy level of agents increases as a result of the literacy campaign, we do not observe a significant correlation between the EEA share and the literacy level in SHEDS, which is why the campaign also has no effect on the EEA share (neither at the aggregate level, as shown in Figure 13 on the left, nor at the cluster level, as shown in Figure 13 on the right).

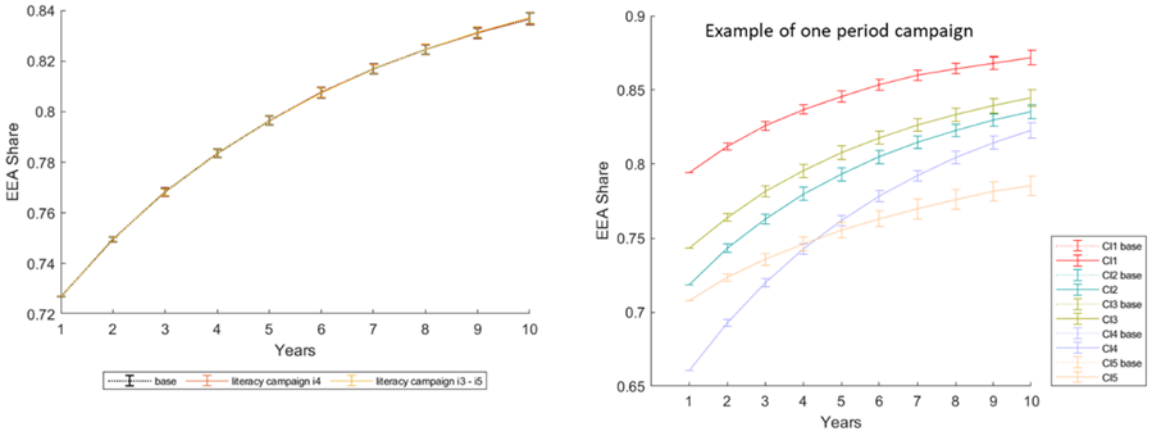


Figure 14: Literacy campaign in the electricity ABM.

Campaign with descriptive norms channel

A campaign which uses the descriptive norms as channel to trigger a change in the preferences for EEAs and consequently the EEA share has a positive impact, at least the way we design the campaign. However, we do not consider whether there is a significant correlation between norms and EEAs in SHEDS, because we do not consider the direct correlation between norms and EEAs. The norms are only used as a channel to transport a message. Looking at the direct correlations between norms and EEA, the results could be different. As shown in Figure 15, in the case of the single-period campaign, the increase in the EEA share compared to the base case starts in period 4, the year in which the campaigns take place. In the case of the multi-period campaign (from period 3 to 5), the increase in the EEA share starts in period 3 and is higher than in the case of a one-year campaign.

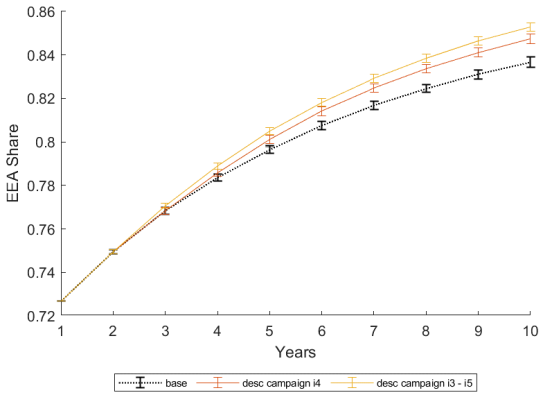


Figure 15: Aggregate effect of a descriptive norms campaign in the electricity ABM.

Which agents respond to the campaign and how is shown in Figure 16. While agents with high levels of descriptive norms (above-average norms, as shown in green in Figure 16 left panel) and high levels of trust (above-average trust, as shown in green in Figure 16 right panel) in the institution launching the campaign (in our case, the SFOE) respond strongly to the campaign, agents with lower descriptive norms and lower levels of trust respond to a much lesser extent.

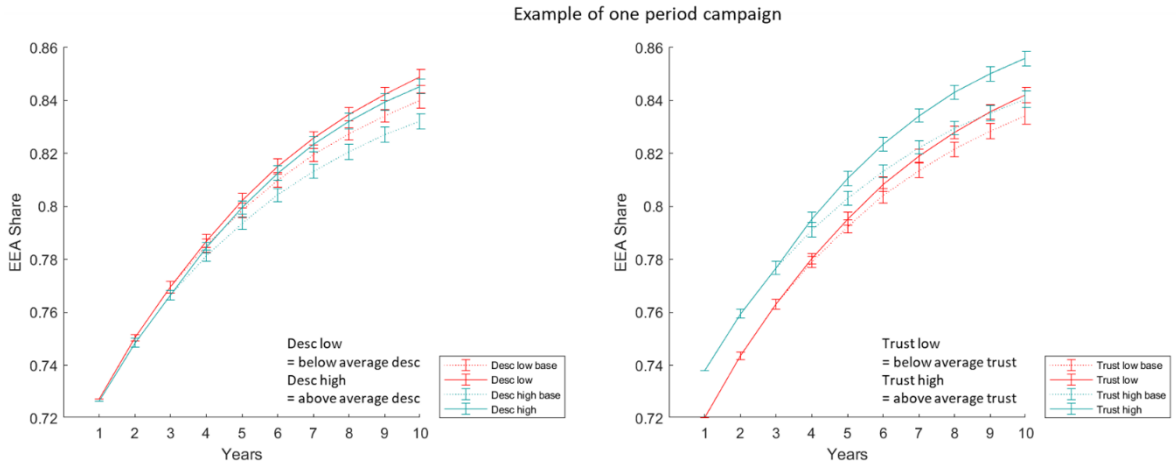


Figure 16: Effect by group of a descriptive norms campaign in the electricity ABM.

Campaign with injunctive norms channel

The campaign using injunctive norms as a channel for sending a message is designed in the same way as the campaign for descriptive norms. The results are also comparable to the descriptive norm scenario, as shown in Figure 17.

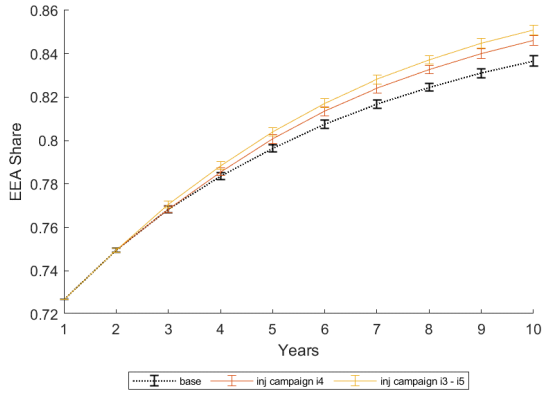


Figure 17: Aggregate effect of an injunctive norms campaign in the electricity ABM.

As with the campaign with descriptive norms, also in the injunctive scenario the agents with higher injunctive norms (and trust) are the ones who respond most strongly to the campaign (Figure 18).

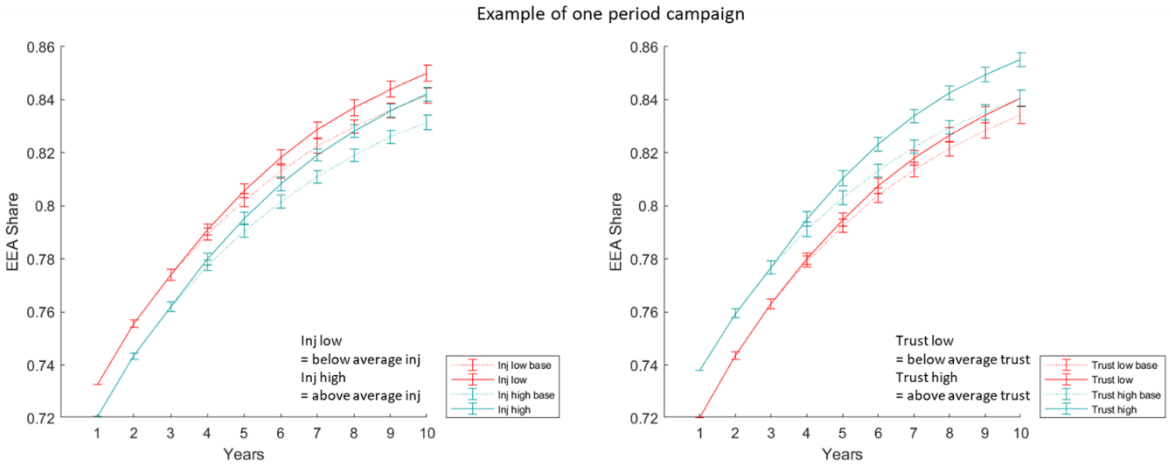


Figure 18: Effect by group of an injunctive norms campaign in the electricity ABM.

Combining measures

While we previously found that both a subsidy and a descriptive norms campaign can have a positive effect on the EEA share of agents, we now analyze the effects when we combine these two measures. As shown in Figure 19, the combination (purple line in the left panel) leads to a further increase in the average EEA share. Thus, compared to a pure subsidy, a slightly larger impact can be achieved by combining measures. However, combining two measures would also result in higher costs compared to a single measure. Moreover, as shown by the green line in Figure 19 (left panel), the combined effect is smaller than the sum of the individual effects.

Looking at the results at the cluster level by comparing the baseline scenario with the combined scenario, we see that all clusters increase their EEA share as a result of the campaign and that a combination of the two measures leads to a higher increase than either measure on its own.

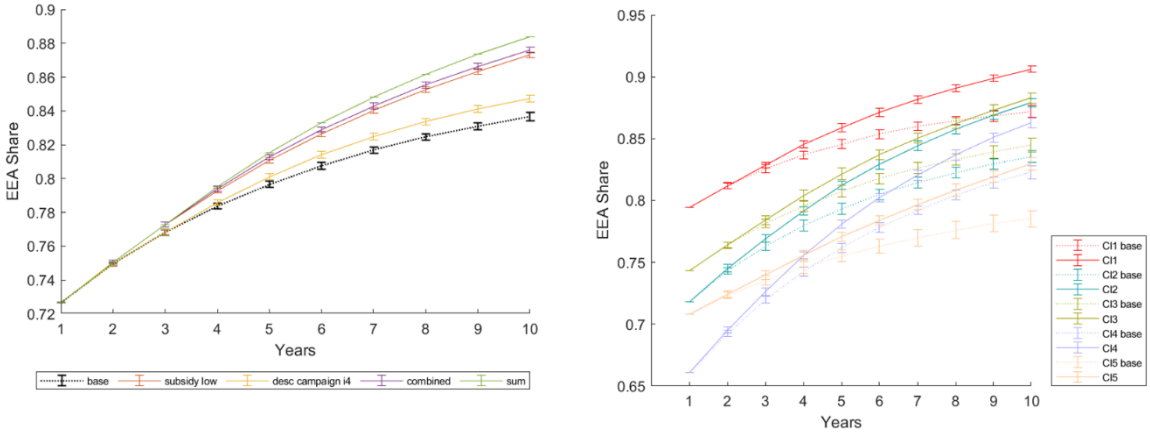


Figure 19: Combined subsidy and descriptive norms campaign in the electricity ABM.

Targeting measures

In a last scenario for the electricity ABM we simulate a targeted norms campaign. For the example of a one-year descriptive norms campaign, we targeted the campaign to specific subgroups (i.e., either individual clusters or two clusters together). Figure 20 shows the EEA share in the base case (black dashed line) compared to the case where all clusters (orange line) and only one or two clusters are targeted simultaneously by the descriptive norms campaign. As the figure on the left shows, the simultaneous threatening of all clusters leads to the largest increase in the average EEA share. However, each individual campaign also has a positive effect, albeit at a lower level, as also shown by the comparison between the case where only cluster 1 is threatened and the case where all clusters are threatened (right panel).

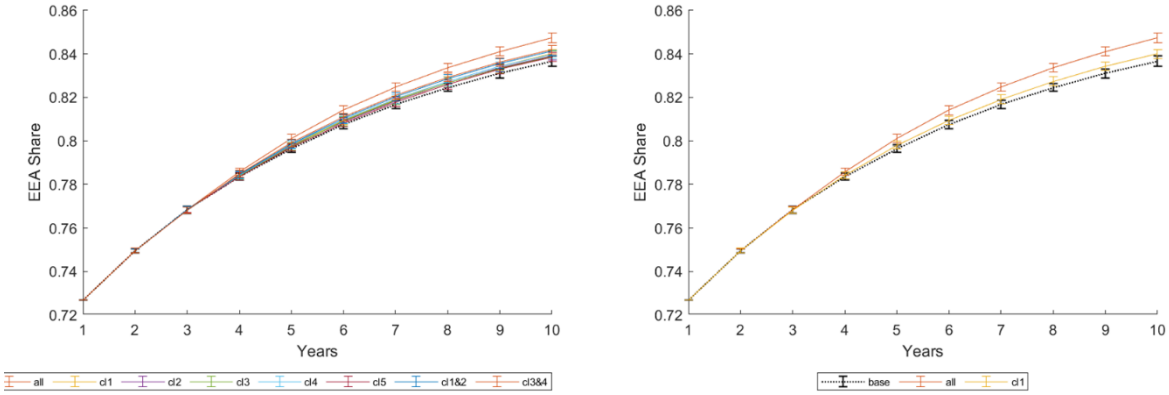


Figure 20: Aggregate effect for a targeted descriptive norms campaign in the electricity ABM.

To obtain a better understanding of the interaction effects, Figure 21 shows the impact of targeting Cluster 1. The left panel shows the base case and the respective EEA share for each cluster when only Cluster 1 is targeted by a campaign. While Cluster 1 (red lines), as the target group, responds strongly to the campaign with an increasing average EEA share, Clusters 2, 3, and 4 also appear to increase

their EEA shares slightly. Thus, it appears that even at low levels, the increase in EEA share spills over to the other clusters due to the exchange of agents in the conversations.

The panel on the right shows the EEA share of Cluster 1 in the base case compared to the case where all clusters are addressed by the campaign and the case where the campaign is targeted to cluster 1. As illustrated, the increase in EEA share for cluster 1 is highest when all households are targeted by the campaign. The difference between the targeted and the general impact can be interpreted as the combined feedback effect from all other clusters on Cluster 1. Consequently, when all households are targeted, the increase in the EEA share has the strongest diffusion effect in the conversations.

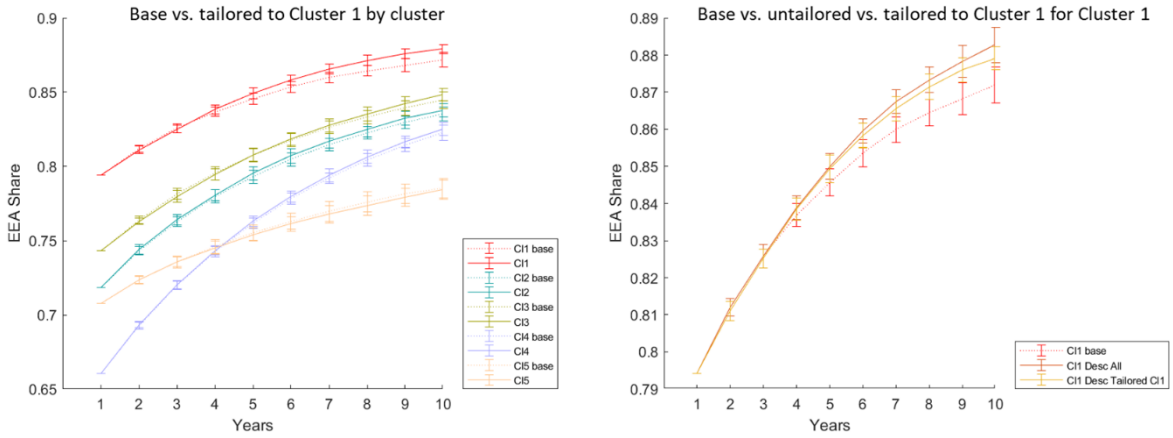


Figure 21: Effect by cluster for a targeted descriptive norms campaign in the electricity ABM.

Heating ABM

In the heat model, the time horizon was extended to 20 years because the simulated decisions are longer-term decisions. In presenting the results of the scenarios for the heating ABM, we focus mainly on the development of the heating systems over time.

As shown in Figure 22 (left panel), the share of non-conventional heating systems initially increases in the base case and then slightly decreases. However, if we look at the development of non-conventional heating systems only for owners (right panel) and thus for the group of actors for whom heating technology is an actual choice variable, we find that the increase in non-conventional heating systems in the first periods is not observed for owners. It is thus driven by the group of renters, for whom, however, the heating technology is not a choice variable (but specified by their landlord). Thus, the initial increase in non-conventional heating systems appears to be a model artifact, as the model requires a few iterations to stabilize. As the base case assumes constant prices, no additional movement towards non-conventional heating systems can be expected after the initial adjustment. The slight decrease is in the range of the confidence intervals (which result from the random shocks) and should thus not be interpreted.

Tax

As a first scenario, we consider a CO2 tax on fossil fuels thus increasing cost of conventional heating technologies. As expected, making non-conventional heating system relatively cheaper increase their share significantly (Figure 22, orange line).

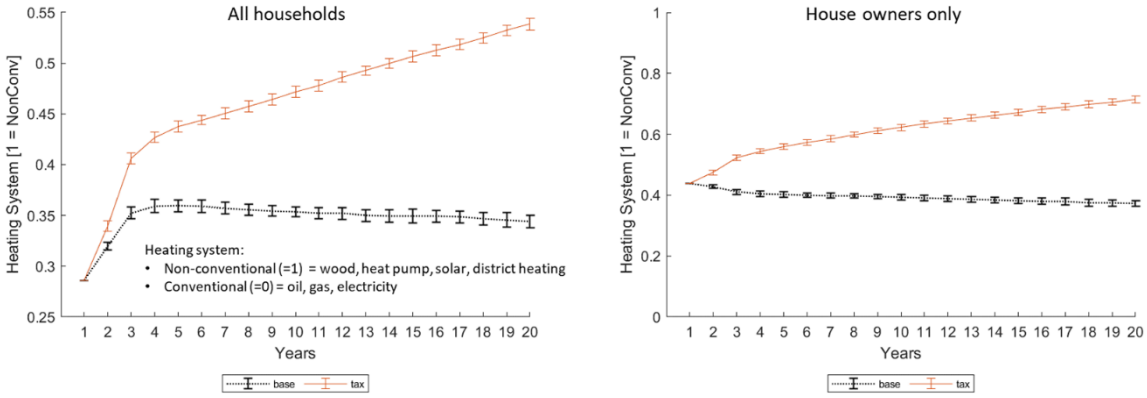


Figure 22: Effect of a tax in the heating ABM.

Subsidy on Non-conventional heating systems and efficiency improvements (windows)

Since the subsidy acts like a reverse tax, the results for the subsidies are similar to the results of the tax. Equating the price of non-conventional and conventional heating systems already leads to a significant increase in the share of non-conventional technologies (orange line in the left panel in Figure 23). If the price is further reduced by a higher subsidy (yellow line), the share of non-conventional heating systems increases further.

Increasing the attractiveness of efficiency improvements through subsidies could affect the age of accommodations (another choice variable in the heating model). However, as shown in Figure 23 on the right, the initial average accommodation age (i.e., the standard “old” vs “renovated” vs “new”) in our sample is already very high (between “renovated” and “new”), which means that many actors are already living in a rather “new” home. Therefore, subsidizing efficiency improvements (windows in our case) may slow the decline in accommodation age somewhat but does not lead to a significant change (also due to the fact that renovation can only lead to a jump from 1 to 2, that is, from “old” to “renovated”, as we are not looking at a complete building renovation here).

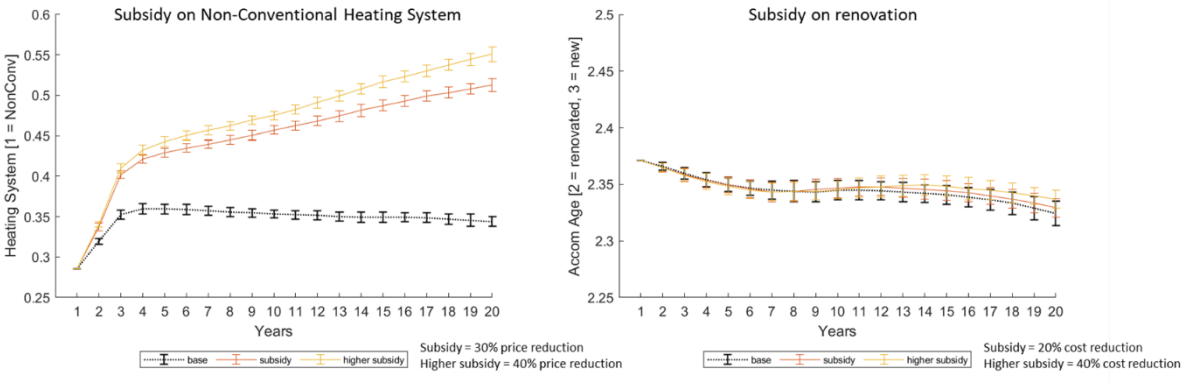


Figure 23: Effect of a subsidy in the heating ABM.

Campaigns: diffusion of information and Literacy campaign

In Figure 24, the results regarding the diffusion of information (left panel) and the literacy campaign (right panel) are shown. As with the ABM for electricity, the results on heating tend to indicate that the two measures do not have a significant impact.

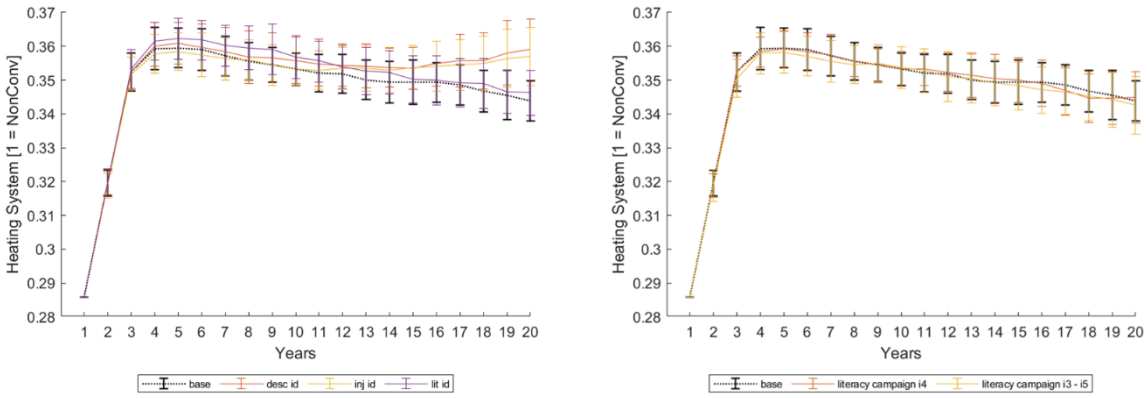


Figure 24: Diffusion of information and literacy campaign in the heating ABM.

Campaign with descriptive and injunctive norms channel

In addition, the results regarding the norms campaigns are consistent with the results of the electricity ABM in that we see a positive effect of both campaigns.

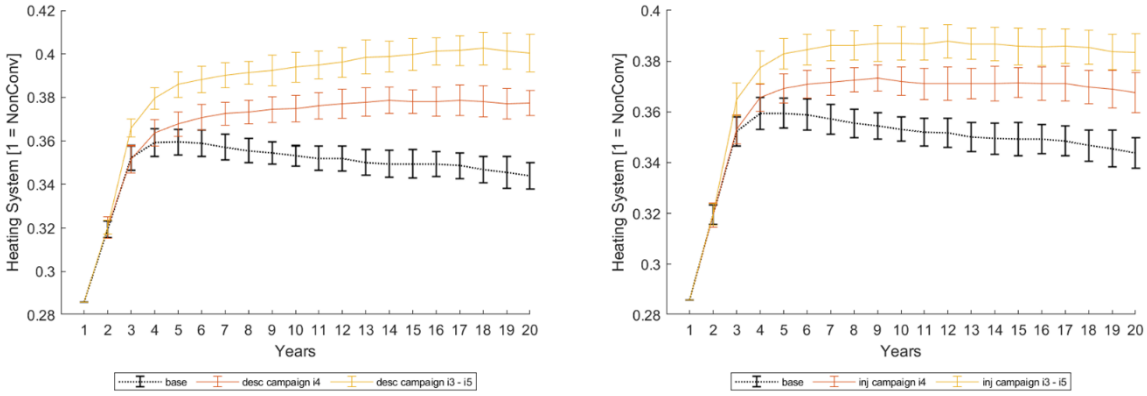


Figure 25: Descriptive and injunctive norms campaigns in the heating ABM.

Combining measures

The results of the heating model are also consistent with the electricity model in terms of the effects of combined measures (even if a tax is considered in combination with a norms campaign instead of a subsidy). Combining the tax and the norms campaign further increases the share of non-conventional heating systems. However, the effect is again not as big as the sum of the individual effects.

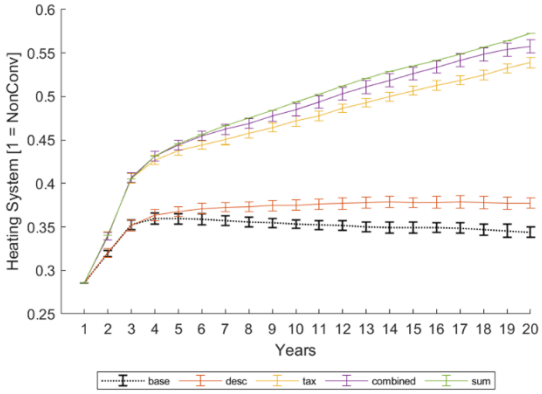


Figure 26: Combined tax and descriptive norms campaign in the heating ABM.

Targeting measures

The targeting of measures to specific subgroups (clusters) again shows that the greatest effect can be achieved if all households are equally addressed by a measure (Figure 27).

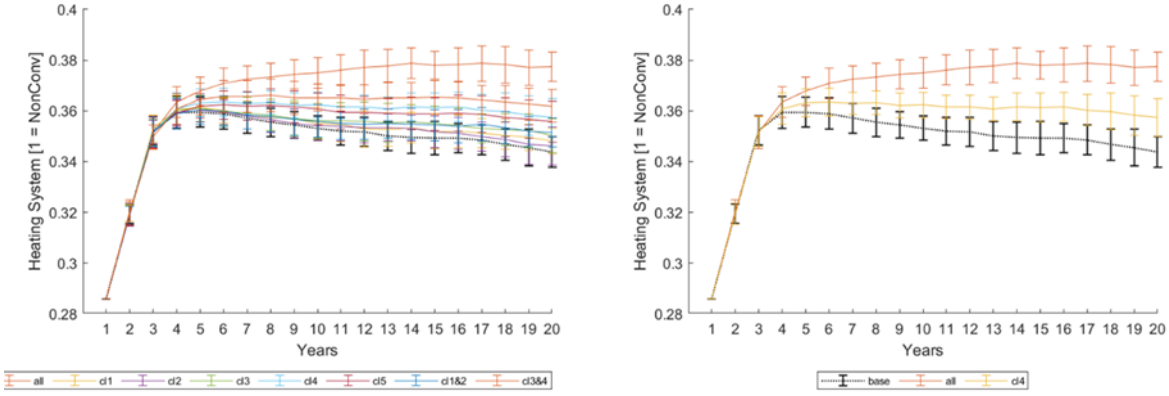


Figure 27: Aggregate effect for a targeted descriptive norms campaign in the heating ABM.

The spillover effects already observed in the electricity model are also confirmed in the heat model. In Figure 28 on the left, only cluster 4 is affected by the measure, but the other clusters also respond. At the same time, considering only cluster 4 (right graph), the effect of a campaign that addresses all groups is also larger for individual groups that are specifically addressed (because of the effect of the conversations).

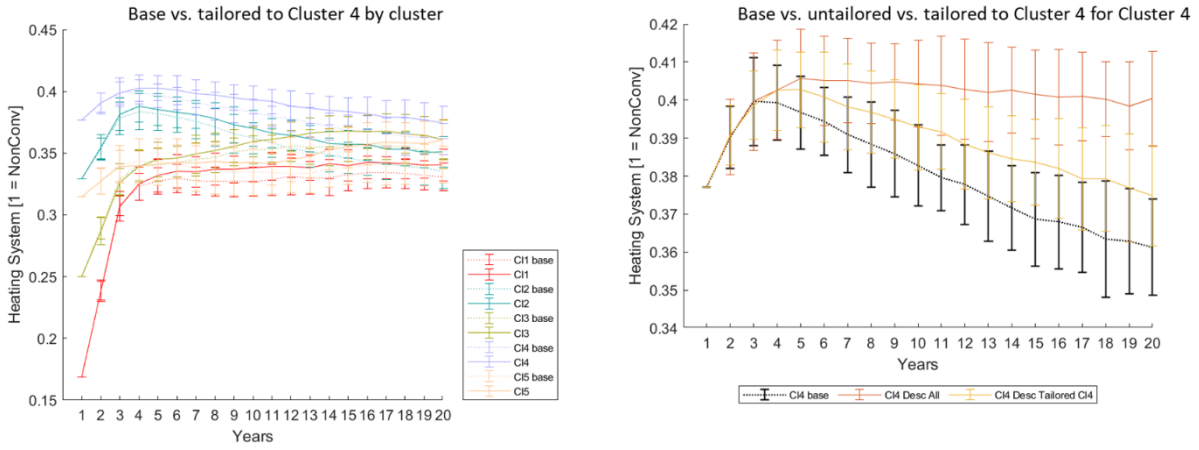


Figure 28: Effect by cluster for a targeted descriptive norms campaign in the electricity ABM

Mobility ABM

In the mobility model, the model horizon is again set at 10 years. In presenting the results of the scenarios for the mobility ABM, we focus mainly on the development of the average number of cars per household over time. As shown in Figure 29, the average number of cars per household in the base case decreases slightly even without measures.

Tax

The introduction of a CO_2 tax makes fuels and thus car trips more expensive, which leads to a decrease in the number of cars.

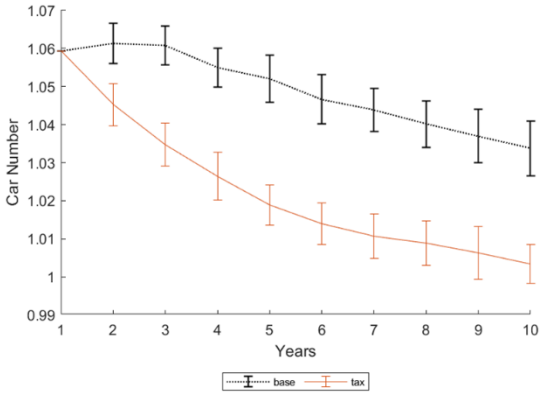


Figure 29: Effect of a tax in the mobility ABM.

Subsidy on electric vehicles

While the average number of cars decreases in the base case, the availability of electric cars also decreases over time. The reason for this is that in the base case, prices are constant, which means that electric vehicles are relatively more expensive than internal combustion vehicles. While electric cars might become relatively cheaper over time, in our case this is not considered. However, since we are only interested in the relative effect of a measure, this is not so problematic here, but should be taken into account when interpreting the figures.

Setting the price of electric vehicles equal to that of internal combustion vehicles through a subsidy will stop the decline in the availability of electric cars (orange line). If they even become cheaper than internal combustion vehicles (subsidy high shown by the yellow line), the number of electric cars will increase significantly over time.

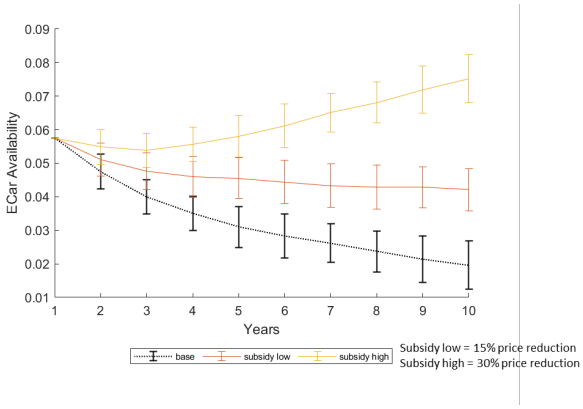


Figure 30: Effect of a subsidy on electric vehicles.

Campaigns: diffusion of information

As for the other two models, the diffusion of information in the case of norms does not show a significant change. However, if a campaign leads to an increase in information exchange and learning through conversations (lit id) as shown in Figure 31 (left panel), this has a positive effect (in terms of a decrease in the number of cars).

If we look at the corresponding development of cars at cluster level (right panel), we see that clusters 1 and 3 in particular show a strong reduction in the number of cars. Cluster 5, on the other hand, shows no change.

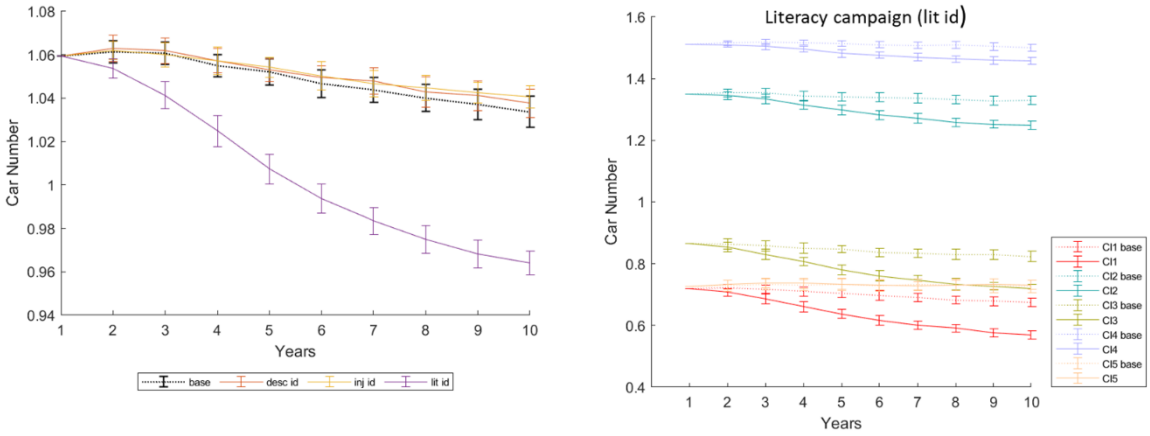


Figure 31: Diffusion of information in the mobility ABM.

Literacy campaign

Although literacy appears to play an important role in the conversations, the simulated literacy campaigns do not show a clear effect (either at the aggregate or cluster level).

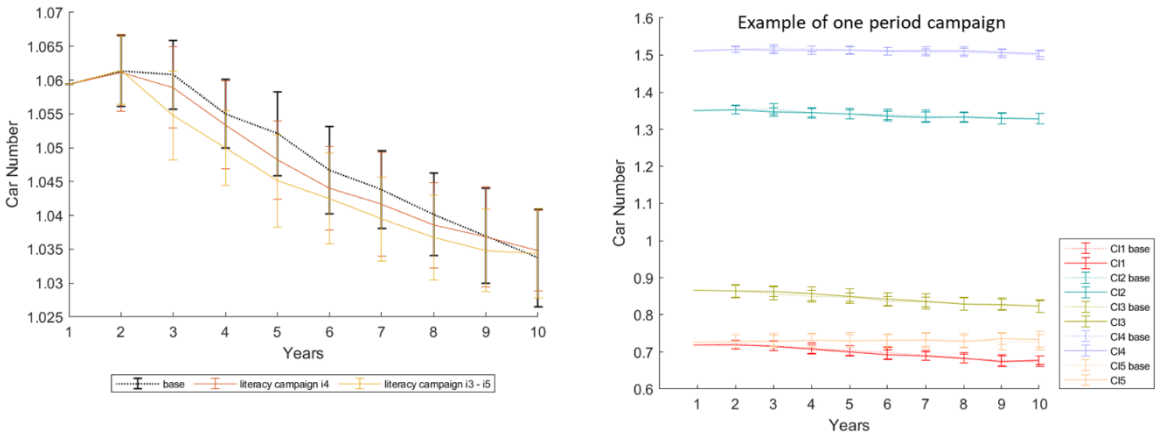


Figure 32: Literacy campaign in the mobility ABM.

Campaign with descriptive and injunctive norms channel

When campaigns use norms as a channel to trigger behavior change, we see the same results, also in the mobility model, in that the number of cars decreases by the campaigns.

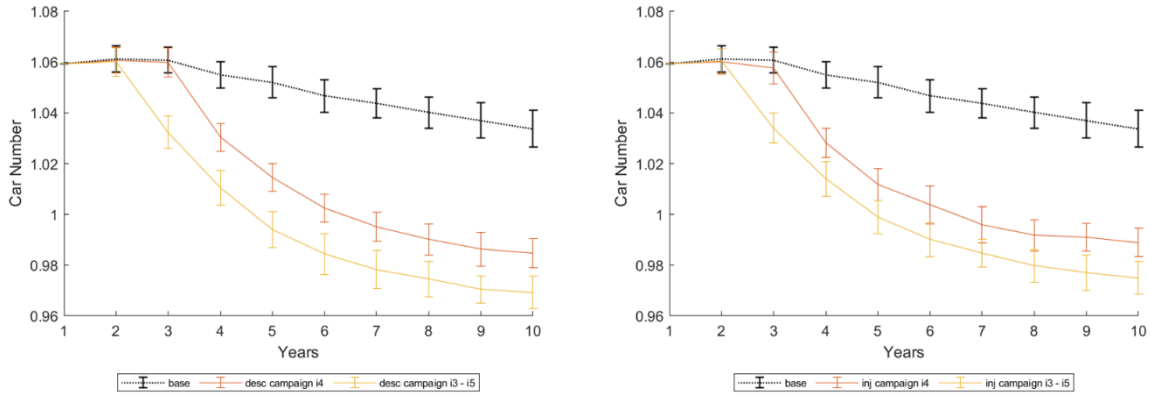


Figure 33: Descriptive and injunctive norms campaigns in the mobility ABM.

Combining measures

The results of the combination of measures in the case of the mobility model also confirms the previous results of the other two models.

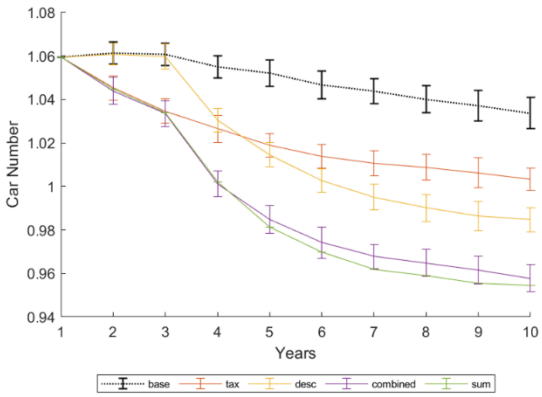


Figure 34: Combined tax and descriptive norms campaign in the mobility ABM.

Targeting measures

The targeting of measures also tends to lead to the same conclusions as in the other models. Less clear, however, is the spillover effect, that is, the effect on other clusters that are not addressed by the measures. As shown in Figure 35 (left panel), there seems to be a small spillover effect from cluster 4 (threated cluster, purple) to 3 (green), but the other clusters tend not to respond.

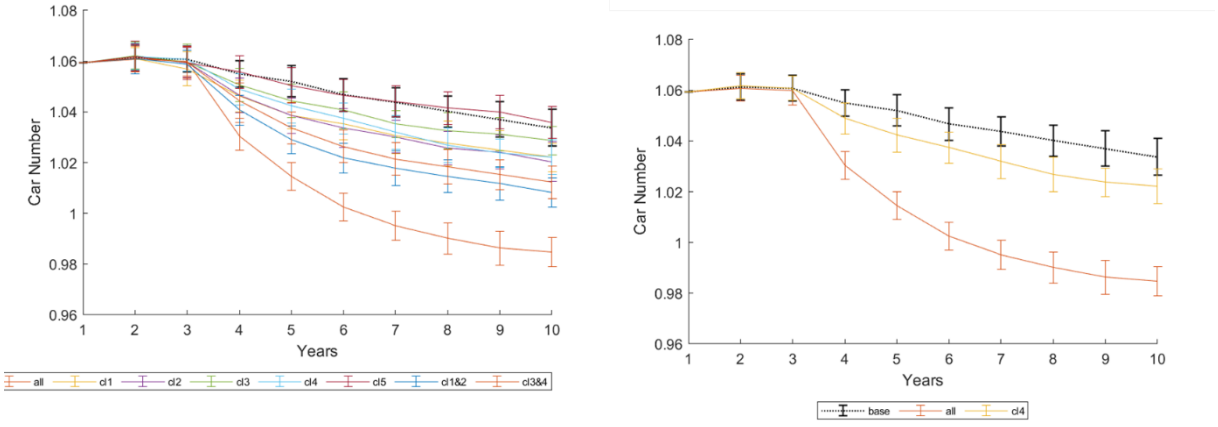


Figure 35: Aggregate effect for a targeted descriptive norms campaign in the mobility ABM.

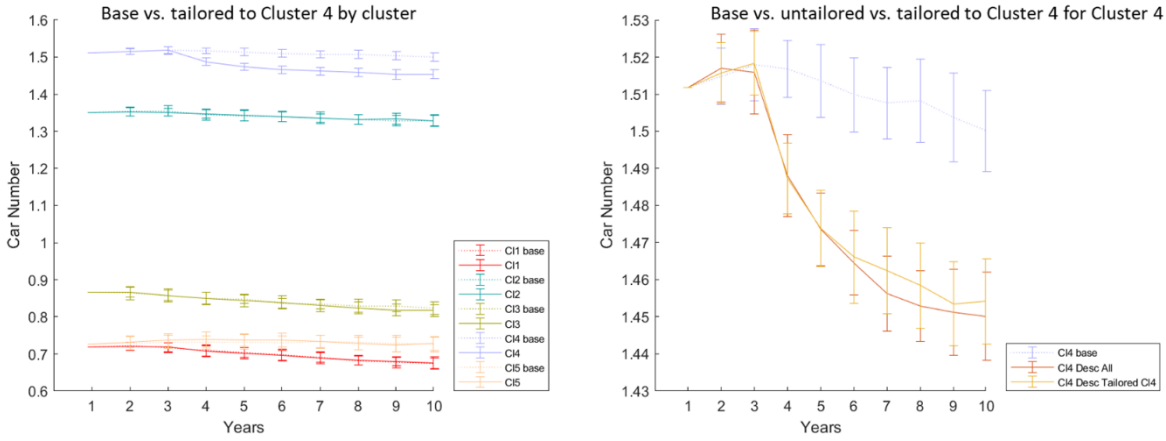


Figure 36: Effect by cluster for a targeted descriptive norms campaign in the mobility ABM.

Results summary for Workstream 2

Table 18 summarizes the results of all three sectors. Across models, monetary measures (hard measures) have all been shown to have the expected effect. With regard to the soft measures, however, the overall results are less clear. Information diffusion campaigns have an effect only in the case of the mobility model and literacy, that is, only if the proportion of conversations in which agents learn from each other and thus increase their literacy level is increased. Otherwise, we see that in our models, literacy campaigns usually have no effect. However, norms campaigns that use norms as a channel to trigger a particular behavior seem promising in their impact, at least in the way we have modeled them.

Combining scenarios can also help to increase the coverage of measures (even if the combined effect is smaller than the sum of the individual effects of the measures). With regard to the targeting of the measures to groups, it can be seen that the greatest effect can be achieved if all households are addressed by a measure. However, if only a specific group is addressed, this can lead to spillover effects (even if in our case rather small) that could be exploited. As the targeted measures where 'targeted' in the sense of addressing only one cluster but not 'tailored' in a sense of increasing the impact/appeal for that cluster, the simulated effects also represent a lower boundary. The same campaigns limited in their dissemination to just one subset of Swiss households can already obtain significant effects. Thus, a more tailored measure could be expected to increase both the direct effect for the targeted cluster but potentially also feedback effects to other clusters.

Table 18: Results summary.

Scenario	**Electricity ABM**	**Heating ABM**	**Mobility ABM**
	Impact (yes, no,?)	Impact (yes, no,?)	Impact (yes, no,?)
Tax	Not considered	Yes (+)	Yes (+)
Subsidy	Yes (+)	Yes (+)	Yes (+)
Information campaign	No	No	Diffusion = Yes (+) Other = No
Descriptive norm campaign	Diffusion = No Channel = Yes (+)	Diffusion = No Channel = Yes (+)	Diffusion = No Channel = Yes (+)
Injunctive norm campaign	Diffusion = No Channel = Yes (+)	Diffusion = No Channel = Yes (+)	Diffusion = No Channel = Yes (+)
Combined scenarios	Combined effect smaller than sum of individual effects		
Targeting of soft measures	Largest effect if all HHs are addressed but small spillover effects		

4 Conclusions

Reducing final energy consumption is an important but ambitious part of the Swiss Energy Strategy. The project and its empirical and model based Workstreams have allowed us to obtain a better understanding of how information and social norms influence energy-related behavior and the performance of monetary incentives.

On the empirical side, the results indicate a significant level of heterogeneity across Swiss households. Literacy, injunctive and descriptive norms do have significant correlations with variables describing energy related investment and usage decisions, but not in a uniform way. The results vary across the three energy types and across household clusters. Whereas many relations are along expected lines, we found some unexpected results as well: For example, sometimes norms and literacy show correlations with energy-related behavior that have different signs and, in some cases, such as mobility investments and the choice of an electricity tariff, the correlation signs of injunctive norms and descriptive norms go in the opposite direction. Overall, the individual results indicate that injunctive norms have a stronger influence on household energy demand than descriptive norms.

The empirical analysis highlights the relevance of the different household types for soft incentives. Within the individual assessment, the strength of the correlation between soft incentives and energy consumption varies across segments. This finding is backed by the municipality analysis that also finds significant differences across clusters for the correlation of social norms and information with mobility related decisions, as well as the choice experiment on home relocation, which shows that the impact of soft instruments varies for the different population segments. Overall, the cluster results indicate that the heterogeneity of Swiss households could benefit from a more targeted approach to using soft measures, or at least from a further investigation of drivers for those differences.

On the modelling side, the simulations highlight that the observed household differences across soft incentives and energy types also translates into different effects on an aggregated level. While the classical monetary policies lead to expected effects, the impact of soft measures is less clear. Nevertheless, soft measures can support the envisioned energy reduction targets; in particular campaigns that use norms as a channel.

In line with the empirical findings, the model simulations show that a more in-depth investigation and representation of heterogeneous actors is central to evaluate different policy options and policy mixes. A singular focus on monetary incentive structures building upon an ‘representative’ consumer does neither reflect the complexity of the different household types, nor does it account for the dynamics between households.

From a practical policy perspective, the project was designed to provide insights along three policy relevant dimensions:

1. To what extent can policies based on soft incentives contribute towards energy reduction targets?
2. How do monetary and non-monetary instruments interact?
3. Are there substantial gains to be expected from tailoring policies? And what kind of tailoring should be considered?

Regarding the first dimension the empirical findings highlight that literary and norms might have an impact on energy behavior and our ABM simulations show that campaigns designed with soft incentives could indeed lead to alterations in investment and usage decisions of households.[19] In general, our results indicate that literacy campaigns are rather limited in their impact. Only in the case of mobility a campaign that leads to an increase in information exchange and learning through conversations has a

[19] As noted in Sect. 2, the results need to be interpreted with care, as they only reveal correlations not “causal” effects.

reducing effect on the number of cars. However, campaigns that use norms as a channel to trigger a particular behavior seem promising in their impact, at least in the way we have modeled them. Overall, soft incentives seem to be able to play a part in the Swiss energy strategy but should not be the only pursued option.

Regarding the interaction of monetary and soft instruments our simulations indicate that there is no negative relation; that is, soft measures do not offset the effect of monetary policies or vice versa. Nevertheless, there is also not a fully additive relationship either. The combined effect of monetary instruments and a norms campaign leads to lower aggregated effects than the sum of the individual measures. Thus, the chosen behavioral representation does not induce (aggregated) positive spillover effects.

Finally, the question on targeting of policies cannot fully be answered yet. While the empirical findings indicate sufficient heterogeneity across households that are a necessary prerequisite for targeting, the simulation results do not provide large scale effects of targeted policies. However, the latter is to a large extend based on the underlying model structure and the limited data available for calibrating the communication process across households. Nevertheless, the simulated targeted approaches already provide indication that a 'reduced form' campaign, that is, targeting only a subset of Swiss households, can already obtain a significant share of a full campaign. Assuming, lower implementation costs for such a targeted campaign a tradeoff between cost and benefit could be identified. For real tailoring, that is, adjusting the campaign content to a specific subset of households to increase the appeal, a better understanding of the dynamics between actors will be needed.

Summarizing, our project shows that for the desired reduction of energy consumption of Swiss households a good understanding of the underlying household behavior is central. While this already holds for monetary incentives, it is even more relevant for soft incentives. Our empirical and model assessments provide a first indication of the potential for policy evaluation when accounting for this heterogeneity and complexity. At the same time our project also provides a novel tool set to identify those dimensions and translate them into a simulation setting to derive aggregated effects for different policy configurations.

5 Outlook and next steps

Our results have implications both for research, in particular for energy economic modeling, and practical implementation.

Implications for modeling household energy demand

The key results reported above provide useful insights to develop a more sophisticated representation of the demand side in energy-economic models. There are three relevant points:

1. Describing household heterogeneity
2. Describing behavior in different domains of energy use
3. Describing policy instruments

The first point (household heterogeneity) is based on the result of this project that there is substantial heterogeneity among households regarding energy-related behavior. This implies that demand-side models could benefit from describing more than a single "representative" household (a setting often used in CGE or energy-system models). A more detailed setting with several household types would allow to track the response to policy measures among households to gain a more detailed picture who

responds how strongly to a given policy. Furthermore, such a model would also facilitate a description of the distributional effects of policy measure. These points are obvious from a theoretical perspective. What our project adds is to show that the differences among households are large enough to expect substantial additional information from a more detailed model.

Furthermore, our results suggest that such heterogeneity should be described in a way that is somewhat uncommon in economic models. Economic models often focus on heterogeneity regarding income. Our results indicate that this may not be the most important dimension for heterogeneity regarding energy-related behavior. Our simulations show that the differences within clusters (where we account for income heterogeneity, described by the error-bars in our graphs) are usually much smaller than the differences between clusters, which describe life situations (phase of life, place of living). Thus, at least in our sample, age and rural vs urban lifestyle appear to be more relevant dimensions for heterogeneity regarding energy-related behavior than income. Based on our results, we would thus suggest to work with a small set of representative households, where each of these households describes a different life situation (e.g., young individual, family, retired couple; rural vs urban place of living).

Comparing the differences between and within our clusters in our simulations indicates that using just a few clusters (such as the 5 clusters used here, or even less) already helps substantially to capture much of the observed heterogeneity.

Of course, there are even more important dimensions (e.g., trust is a key dimension for norm-based campaigns). However, without a very detailed data source (such as SHEDS), information about such dimensions is usually not available. Thus, describing such dimensions will simply not be feasible in most cases.

Regarding the second point (describing behavior in different domains of energy use), our empirical results strongly suggest that different domains of energy use require different modeling approaches. The key determinants for mobility differ strongly from those for electricity and both differ from those for heat. This has been a major reason for building different agent-based models in this project that use different dimensions to describe households (e.g., the mobility model includes the number of workers per household, whereas the heat model distinguishes tenants and owners, both variables are not of comparable relevance for electricity). Furthermore, our results show that different household types react differently to policy measures in the different domains of energy use.

These points imply that it is not only important to capture different households but also to capture different uses of energy within the different households. Again, it is clear that some differences in behavior and responses to policy measures have to be expected between, for example, the domains of heat and mobility. What this project adds is to show that these differences matter quantitatively and to provide some insight which determinants are important for which domain of energy use.

Regarding the third point (describing policy measures), a key result of this project is that information and norms correlate with energy-related behavior for some types of households (cf. Table 7). This implies that capturing information- and norm-based policies in models used for policy analysis could be important. Furthermore, there is some interaction of such policies with monetary incentives, which strengthens the case for including soft policy measures in policy-assessment models, as soft instruments are widely used. Not taking these policies into account might result in a distorted picture of the effects of monetary incentives in model-based policy assessments.

All these points indicate that energy-economic modeling could benefit from using somewhat more complex models, using several instead of a single representative household(s), describing different uses of energy, and covering not only prices as possible ways to influence household energy use. However, our results indicate that already small steps in these directions could provide substantial benefits. It is possible to enhance the demand-side representation of energy-economic models in comparatively simple ways by including a small number of different household types based on easily available data and by distinguishing just a few types of energy uses.

What is somewhat more difficult is to cover a broader set of policy measures that includes soft measures is more demanding, as this requires survey data. Thus, this might not be feasible in all types of models.

Finally, from a general perspective, the results of the project highlight that much can be gained by using somewhat more complex models and that this requires somewhat better data. Establishing a continuous survey on energy use that has a sufficient number of respondents to capture heterogeneity among households, that covers all important domains of energy use in a single survey, and that provides some information that is useful for describing soft policy measures, such as, energy literacy, susceptibility to peer pressure, and trust in providers of energy-related information could be an important step towards building better models.

Implications for policy implementation

Regarding practical implementation, the insight that policies that target only a subgroup of the population (e.g., a single cluster, such as young people living in a city) can already deliver substantial impacts, if the subgroup is well-chosen has direct implications. Given that soft measures, such as information- or norm-based campaigns, can easily target subgroups, such an approach might yield a better cost/benefit ratio than non-targeted policies. The example in Section 3 highlights this quite nicely: Campaigns to reduce car ownership have, according to our data, a substantial effect on some clusters (e.g., Clusters 1 (young urban), 2 (young rural), and 3 (middle-aged urban)) but only a very small effects on others (e.g., Cluster 5 (retired)). Our results indicate that, on the aggregate level, a targeted campaign has always smaller impact (even on the treated clusters), but the reduced impact has to be compared to the cost savings of addressing only a subgroup (e.g., only people living in a city or only young people). Whenever the costs of a campaign scale (close to) linearly with the addressed number of people, it is likely that having several targeted campaigns would deliver more impact in terms of energy saving at the same cost as a single, population-wide campaign.

However, it should be stated clearly that our results can indicate that targeted policy measures could be beneficial but that our results are not on the level of detail that would be required to select optimal target groups for the different domains of energy use and the different campaign channels (information vs descriptive norms vs injunctive norms). To this end, more and more detailed data would be required.

6 National and international cooperation

The project was carried out within the SCCER CREST framework and exchange with researchers from CREST took place throughout the project's duration. In particular, 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 (Paul Burger, Iljana Schubert, Annika Sohre) and from the Zurich University of Applied Sciences (Bernadette Sütterlin, Uros Tomic). Furthermore, we obtained price information for the choice experiment from Fahrländer Partner AG, a space development consultancy in Zurich.

7 Communication

The project results have been presented at the following national and international workshops and conferences:

- Energy Modelling Platform for Europe (EMP-E) 2018 – Modelling clean energy pathways (Presenter: Florian Kuhlmey).
- 13th International Workshop on "Empirical Methods in Energy Economics" (EMEE) 2020, Poster, „Tailored interventions in a major life decision: A home relocation discrete choice experiment", (Presenter: Joëlle Velvart)
- 25th EAERE Annual Conference 2020, Presentation, „Tailored interventions in a major life decision: A home relocation discrete choice experiment", (Presenter: Joëlle Velvart)
- Annual Congress of the Swiss Society of Economics and Statistics (SSES/SGVS) 2021, Presentation, „Tailored interventions in a major life decision: A home relocation discrete choice experiment", (Presenter: Joëlle Velvart)

In addition, the project has been discussed and presented at several SCCER CREST meetings.

8 Publications

The publications on the choice experiment on ttailored intervention for home relocation is available as working paper on the University Basel research database (Velvart et al., 2022, Link). An empirical as well as a model centered publication presenting the main findings of the projects are scheduled for Spring 2023.

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10 Appendix

10.1 Energy Literacy Index

1. What do you think the top rating of the energy label for cars stands for?
    - An overall low amount of fuel consumption compared to all other vehicles in the market.
    - A low amount of fuel consumption compared to other similar vehicles.
2. How much do you think it costs in terms of electricity to run the following devices? (Amounts in cents)

	0-19	20-39	40-59	60-79	80-100	More than 100	I do not know
a) A desktop computer for 1 hour							
b) A washing machine (load of 5kg at 60°C)							

3. Which of the following consumes more energy?
    - Producing 1kg of beef
    - Taking a warm bath
    - Both consume about the same
    - I do not know
4. Indicate whether the following statements are true or false.

	True	False	I do not know
a) The biggest share of energy consumed in a Swiss household is for heating purposes.			
b) CO2 emissions play a crucial role in global warming.			
c) Simply lowering the heating temperature in an average household by 1°C can help to cut down the heating demand by 6%.			
d) Coal is a renewable energy resource.			
e) Hydroelectric power plants account for 10% of total Swiss electricity production.			

5. Do you believe that energy prices will decrease or increase in the future?

	Significant decrease	Decrease	No decrease or increase	Increase	Significant increase	I don't know
a) Oil price						
b) Electricity price						

10.2 Estimation Results ABM Specifications

Table 19: Non-conventional heating system estimation results for the full sample and the five clusters

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.02*	0.01	0.04*	0.05*	0.00	0.01
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
Constant	-1.24***	-1.72***	-1.92***	0.28	-1.01*	-0.47
	(0.21)	(0.50)	(0.49)	(0.59)	(0.53)	(1.04)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Socio-demographics	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Accommodation controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6216	1513	1215	1149	1525	790
Log Likelihood	-3138.6	-590.3	-631.9	-532.1	-869.5	-396.8

Note: Standard errors in parenthesis. * p < 0.10, ** p < 0.05, *** p < 0.01. Probit model. Socio-demographics (individual level) are age, gender, education, Swiss citizenship. Household-level controls are household size, income, household type, place of living, home ownership. Accommodation controls are accommodation type, age.

Table 20: Estimation models of EA and electricity usage for the full sample and with cluster-specific parameters

	EA		Electricity usage	
	Full sample	Clusters	Full sample	Clusters
Energy literacy	-0.04***		-0.02	
	(0.01)		(0.01)	
Energy literacy: Cl 1		-0.05***		0.02
		(0.02)		(0.03)
Energy literacy: Cl 2		-0.01		-0.07***
		(0.02)		(0.03)
Energy literacy: Cl 3		-0.06***		-0.02
		(0.02)		(0.02)
Energy literacy: Cl 4		-0.05***		-0.02
		(0.01)		(0.02)
Energy literacy: Cl 5		-0.03		-0.01
		(0.03)		(0.03)
Injunctive norms	-0.02		-0.04*	
	(0.02)		(0.02)	
Injunctive norms: Cl 1		-0.09***		-0.13**
		(0.03)		(0.06)
Injunctive norms: Cl 2		-0.01		-0.01
		(0.03)		(0.06)
Injunctive norms: Cl 3		-0.02		-0.03
		(0.03)		(0.06)
Injunctive norms: Cl 4		0.04		-0.04
		(0.03)		(0.04)
Injunctive norms: Cl 5		0.02		-0.01
		(0.05)		(0.05)
Descriptive norms			0.03	
			(0.03)	
Descriptive norms: Cl 1				0.02
				(0.07)
Descriptive norms: Cl 2				0.10
				(0.06)
Descriptive norms: Cl 3				0.01
				(0.07)
Descriptive norms: Cl 4				0.04
				(0.04)
Descriptive norms: Cl 5				-0.04
				(0.05)
Constant	3.50***	3.87***	5.31***	5.26***
	(0.20)	(0.22)	(0.38)	(0.40)
Canton controls	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes
Socio-demographics	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
Accommodation controls	No	No	Yes	Yes
EA control	No	No	Yes	Yes
Electricity controls	No	No	Yes	Yes
Observations	4545	4545	1237	1237
R squared	0.31	0.32	0.54	0.55

Note: Standard errors in parenthesis. * p < 0.10, ** p < 0.05, *** p < 0.01. OLS estimates.

Table 21: Estimation results of the Heckman sample selection model for EEA (full sample & clusters)

	Full sample		Clusters	
	EEA	Know label	EEA	Know label
Energy literacy	-0.09***	0.07***		
	(0.02)	(0.01)		
Energy literacy: Cl 1			-0.07***	0.06***
			(0.02)	(0.02)
Energy literacy: Cl 2			-0.11***	0.05**
			(0.03)	(0.02)
Energy literacy: Cl 3			-0.11***	0.10***
			(0.03)	(0.02)
Energy literacy: Cl 4			-0.08***	0.08***
			(0.03)	(0.02)
Energy literacy: Cl 5			-0.11***	0.08**
			(0.04)	(0.03)
Injunctive norms	-0.01	0.07***		
	(0.03)	(0.02)		
Injunctive norms: Cl 1			-0.09	0.04
			(0.06)	(0.04)
Injunctive norms: Cl 2			0.16**	0.04
			(0.07)	(0.05)
Injunctive norms: Cl 3			-0.05	0.09*
			(0.07)	(0.05)
Injunctive norms: Cl 4			-0.07	0.15***
			(0.07)	(0.05)
Injunctive norms: Cl 5			0.02	0.06
			(0.10)	(0.08)
Descriptive norms	0.06**	0.01		
	(0.03)	(0.02)		
Descriptive norms: Cl 1			0.11*	0.02
			(0.06)	(0.04)
Descriptive norms: Cl 2			-0.07	0.08*
			(0.07)	(0.05)
Descriptive norms: Cl 3			0.11*	-0.03
			(0.07)	(0.05)
Descriptive norms: Cl 4			0.08	-0.06
			(0.06)	(0.05)
Descriptive norms: Cl 5			0.06	0.01
			(0.10)	(0.08)
athrho	-1.09***		-1.11***	
	(0.09)		(0.10)	
lnsigma	0.51***		0.51***	
	(0.02)		(0.02)	
Constant	3.10***	0.05	3.05***	0.22
	(0.35)	(0.22)	(0.39)	(0.25)
Canton controls	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes
Socio-demographics	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
Accommodation controls	Yes	No	Yes	No

Observations	4541	4541
Nonselected	1290	1290
Selected	3251	3251
Log Likelihood	-8223.2	-8203.0
Rho	-0.80	-0.81
Sigma	1.67	1.67
Lambda	-1.33	-1.35

Note: Standard errors in parenthesis. * p < 0.10, ** p < 0.05, *** p < 0.01. “Know label” is the selection equation and reflects knowledge of the energy labels of EA.

Table 22: Estimation results number of public transport tickets (full sample and cluster models)

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.01**	0.01	0.03***	-0.01	0.02**	0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Injunctive norms	0.06***	0.03	0.06***	0.04*	0.06**	0.03
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Descriptive norms	-0.04***	-0.00	-0.05**	-0.05*	-0.07**	0.01
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Constant	-0.40***	0.19	0.32	-0.24	-1.03***	-0.57
	(0.12)	(0.28)	(0.25)	(0.28)	(0.28)	(0.47)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Socio-demographics	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
MoT controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6216	1569	1199	1120	1475	853
R squared	0.37	0.38	0.47	0.39	0.41	0.36

Note: Standard errors in parenthesis. * p < 0.10, ** p < 0.05, *** p < 0.01. OLS estimates.

Table 23: Estimation results electric car (full sample and clusters)

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.13**	0.17	0.09	0.52	0.12	0.54*
	(0.06)	(0.14)	(0.13)	(0.41)	(0.11)	(0.31)
Injunctive norms	0.02	-0.17	-0.11	3.67***	-0.07	-0.28
	(0.14)	(0.37)	(0.30)	(1.19)	(0.27)	(0.70)
Descriptive norms	-0.04	-0.29	-0.21	1.55*	-0.26	-0.30
	(0.14)	(0.33)	(0.32)	(0.86)	(0.32)	(0.59)
Constant	-5.18***	-5.78	-10.13***	-54.82***	-9.55***	52.74**
	(1.42)	(5.09)	(3.09)	(19.06)	(3.07)	(20.67)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Socio-demographics	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1942	296	369	141	443	130
Log Likelihood	-362.7	-55.9	-77.7	-18.8	-80.3	-22.0

Note: Standard errors in parenthesis. * p < 0.10, ** p < 0.05, *** p < 0.01. Logit model. Sample restricted to cars purchased in the last three years.

Table 24: MoT work (public vs. private transport) estimation results (full sample and five clusters)

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.08***	0.12***	0.07*	0.09*	0.10***	0.11
	(0.02)	(0.04)	(0.04)	(0.05)	(0.04)	(0.22)
Injunctive norms	0.18***	0.16*	0.10	0.36***	0.24***	0.98**
	(0.04)	(0.09)	(0.09)	(0.11)	(0.09)	(0.47)
Descriptive norms	-0.09**	0.03	-0.11	-0.16	-0.21**	-1.01**
	(0.04)	(0.09)	(0.09)	(0.11)	(0.09)	(0.43)
Constant	-0.16	0.61	1.82*	-0.30	-2.33**	-2.39
	(0.42)	(1.00)	(1.01)	(1.21)	(1.06)	(5.88)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Socio-demographics	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Commuting distance	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3810	1073	921	679	1007	96
Log Likelihood	-2323.1	-513.0	-542.3	-373.3	-596.9	-46.7

Note: Standard errors in parenthesis. * p < 0.10, ** p < 0.05, *** p < 0.01. Logit estimation. MoT work takes the value 1 for public transport and the value 0 for private transport.

Table 25: MoT leisure (public vs. private transport) estimation results (full sample and five clusters)

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.11***	0.15***	0.11***	0.12***	0.09**	0.03
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
Injunctive norms	0.27***	0.29***	0.22**	0.19**	0.38***	0.30***
	(0.04)	(0.07)	(0.10)	(0.08)	(0.09)	(0.11)
Descriptive norms	-0.16***	-0.10	-0.11	-0.16*	-0.22**	-0.26**
	(0.04)	(0.07)	(0.09)	(0.09)	(0.09)	(0.11)
Constant	-0.20	-0.10	1.67*	-0.47	-3.07***	-0.31
	(0.35)	(0.81)	(0.90)	(0.94)	(1.06)	(1.60)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Socio-demographics	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5448	1231	1098	951	1357	795
Log Likelihood	-3103.1	-731.9	-546.3	-580.3	-625.9	-483.6

Note: Standard errors in parenthesis. * p < 0.10, ** p < 0.05, *** p < 0.01. Logit estimation. MoT leisure takes the value 1 for public transport and the value 0 for private transport.

10.3 Correlation Analysis: Descriptive Statistics and Covariates

Table 26: Descriptive statistics SHEDS

	Mean	SD	Min	Max
Age	43.94	15.18	20	88
Age (household)	43.54	14.33	19	88
Female	0.55	0.50	0	1
Education in years	13.93	2.01	7	16
Income up to 3'000 CHF	0.07	0.26	0	1
Income 3'000-4'459 CHF	0.10	0.30	0	1
Income 4'500-5'999 CHF	0.16	0.36	0	1
Income 6'000-8'999 CHF	0.28	0.45	0	1
Income 9'000-12'000 CHF	0.21	0.41	0	1
Income 12'000 + CHF	0.17	0.38	0	1
Household size	2.28	1.29	1	19
Single person household	0.29	0.45	0	1
Couple without children	0.33	0.47	0	1
Couple with children	0.24	0.43	0	1
Single parent with one or more children	0.05	0.21	0	1
Patchwork family	0.03	0.18	0	1
Non-family shared household	0.06	0.24	0	1
Urban	0.50	0.50	0	1
Rural	0.50	0.50	0	1
Citizenship	0.90	0.30	0	1
Home ownership	0.32	0.47	0	1
Young urban	0.25	0.44	0	1
Young rural	0.20	0.40	0	1
Mid-age urban	0.18	0.39	0	1
Mid-age rural	0.23	0.42	0	1
Senior	0.13	0.33	0	1
Energy literacy	6.29	1.98	0	10
Injunctive norms	3.26	0.98	1	5
Descriptive norms	3.31	0.94	1	5
Number of observations	7724			

Table 27: Covariates of investment behavior models

	Investment Choices			
I	**Variable**	**Model**	**Socio-demographics**	**Variable-specific**
Mobility	GA	Poisson	• Age • Gender • Education • Citizenship (Swiss vs. other) • Household size • Household type • Home ownership • Spatial place of living • Canton of residence	
	HTA	Poisson		
	RA	Poisson		
	Cars	Poisson		
	Motorbike	Poisson		
	Bike	Poisson		
	E-bike	Poisson		
	Electric	Probit		
Heat	Heating	Multinomial logit, probit		• Accommodation age • Accommodation type • Minergie • Renovations
	Warm water	Multinomial logit, probit		
Electricity	Number	Poisson		
	Label	Ordered Probit		
	Know label	Probit		
	Tariff change	Probit		

Table 28: Covariates of usage behavior models

	Usage Choices			
	Variable	**Model**	**Socio-demographics**	**Variable-specific**
Mobility	Work	Multinomial Logit	• Age • Gender • Education • Citizenship (Swiss vs. other) • Household size • Household type • Home ownership • Spatial place of living • Canton of residence	
	Leisure	Multinomial Logit		
	Grocery	Multinomial Logit		
	Self-assessed	Ordered Probit		
	Odometer	OLS		
	Flight costs	OLS		
	Number of flights	Negative binomial		
Heat	Heating costs	OLS (Log-Lin)		• Accommodation age • Accommodation type • Accommodation size in m^2 (ln) • Minergie • Renovations • Number of rooms, bathrooms and other (i.e. garage) • Heating and warm water systems
	Temperature	OLS		
	Index	Poisson		
	Venting	Ordered Probit		
	Shower/Baths	OLS		
	Turn off shower	Ordered Probit		
Electricity	Switch off	OLS		
	Frequency (per week)	OLS (Log-Lin)		
	Duration (h/day)	OLS (Log-Lin)		
	Costs	OLS (Log-Lin)		• Accommodation age • Accommodation type • Accommodation size in m^2 (ln) • Number of rooms, number of bathrooms, number of other rooms (i.e. garage) • Solar thermal panels • Photovoltaic panels • Electric heating and warm water • Minergie
	Usage	OLS (Log-Lin)		

10.4 Estimation Results Correlation Analysis

Table 29: Number of GAs

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.07***	0.03	0.05*	0.07**	0.12***	0.02
	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Injunctive norms	0.17***	0.10**	0.23***	0.09	0.15**	0.29***
	(0.03)	(0.04)	(0.06)	(0.06)	(0.06)	(0.08)
Descriptive norms	-0.10***	-0.02	-0.20***	-0.02	-0.15***	-0.11
	(0.02)	(0.04)	(0.06)	(0.05)	(0.06)	(0.08)
Age (household)	-0.01***	-0.02*	-0.02	-0.01*	-0.04***	-0.02
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	0.07***	0.10***	0.21***	0.12**	0.16***	0.11
	(0.02)	(0.03)	(0.04)	(0.06)	(0.04)	(0.09)
Education in years	0.00	0.02	0.03	0.01	0.00	0.06*
	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Income 3'000-4'459	-0.05	0.09	-0.29	0.24	0.31	-0.06
	(0.11)	(0.19)	(0.24)	(0.39)	(0.40)	(0.25)
Income 4'500-5'999	-0.11	-0.18	-0.42**	0.51	0.29	-0.02
	(0.10)	(0.14)	(0.21)	(0.37)	(0.39)	(0.26)
Income 6'000-8'999	-0.04	-0.19	-0.45**	0.60*	0.75**	0.01
	(0.09)	(0.14)	(0.18)	(0.36)	(0.37)	(0.26)
Income 9'000-12'000	-0.03	-0.18	-0.66***	0.76**	0.89**	0.14
	(0.10)	(0.15)	(0.22)	(0.36)	(0.37)	(0.28)
Income 12'000 or more	0.25**	0.14	-0.17	1.06***	1.12***	-0.37
	(0.10)	(0.15)	(0.22)	(0.37)	(0.37)	(0.37)
Couple without children	0.42***	0.58***	0.21	0.26*	0.16	0.29*
	(0.07)	(0.13)	(0.16)	(0.16)	(0.18)	(0.18)
Couple with children	0.45***	0.51***	-0.24	0.12	0.22	0.36
	(0.09)	(0.15)	(0.22)	(0.23)	(0.19)	(0.29)
Single parent with one or more children	0.66***	0.49**	0.61**	0.57***	0.35	-0.08
	(0.11)	(0.23)	(0.29)	(0.21)	(0.26)	(0.46)
Patchwork family	0.39***	0.11	0.13	0.23	-0.18	0.63
	(0.15)	(0.39)	(0.37)	(0.28)	(0.28)	(0.67)
Non-family shared household	0.85***	0.95***	0.65***	0.07	0.54**	0.10
	(0.09)	(0.14)	(0.21)	(0.27)	(0.26)	(0.33)
Swiss	0.28***	0.41***	0.47**	0.36*	0.06	0.04
	(0.08)	(0.13)	(0.19)	(0.19)	(0.20)	(0.32)
Agglomeration	-0.22***					-0.27**
	(0.06)					(0.14)
Countryside	-0.39***		-0.17		-0.08	-0.44**
	(0.07)		(0.13)		(0.10)	(0.18)
Female	0.01	-0.15*	0.04	0.01	0.23**	0.05
	(0.05)	(0.08)	(0.11)	(0.11)	(0.10)	(0.13)
Owner	0.15**	0.08	0.19	0.14	-0.12	-0.01
	(0.06)	(0.17)	(0.14)	(0.12)	(0.11)	(0.12)

Constant	-2.08***	-1.89***	-2.18***	-2.58***	-1.54**	-1.45
	(0.25)	(0.51)	(0.59)	(0.64)	(0.75)	(0.95)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7451	1893	1525	1356	1700	921
Log-likelihood	-6155.8	-1620.4	-1102.4	-1119.0	-1318.7	-711.0

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Poisson estimation

Table 30: Number of Half fare cards

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.02***	0.03***	0.02	0.03*	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Injunctive norms	0.00	-0.01	-0.00	0.03	0.03	-0.02
	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Descriptive norms	0.01	0.03	-0.02	-0.01	0.05*	-0.07*
	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Age (household)	0.00**	0.01**	0.01**	-0.01**	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Household size	0.04**	0.12***	0.02	0.04	0.07***	-0.04
	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.08)
Education in years	0.03***	0.05***	0.04***	0.02	0.03***	-0.00
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Income 3'000-4'459	-0.02	-0.15	-0.24	0.08	0.36**	0.05
	(0.06)	(0.11)	(0.15)	(0.13)	(0.17)	(0.13)
Income 4'500-5'999	0.04	-0.02	-0.15	0.09	0.40**	0.06
	(0.05)	(0.09)	(0.12)	(0.13)	(0.17)	(0.13)
Income 6'000-8'999	0.10**	0.04	-0.11	0.14	0.52***	0.11
	(0.05)	(0.08)	(0.12)	(0.12)	(0.16)	(0.13)
Income 9'000-12'000	0.18***	0.09	0.05	0.07	0.58***	0.22
	(0.05)	(0.09)	(0.13)	(0.13)	(0.17)	(0.15)
Income 12'000 or more	0.19***	0.13	-0.01	0.12	0.56***	0.26
	(0.06)	(0.09)	(0.13)	(0.13)	(0.17)	(0.18)
Couple without children	0.42***	0.32***	0.40***	0.41***	0.38***	0.62***
	(0.03)	(0.06)	(0.09)	(0.08)	(0.07)	(0.11)
Couple with children	0.51***	0.09	0.44***	0.67***	0.40***	0.50**
	(0.06)	(0.09)	(0.12)	(0.11)	(0.10)	(0.23)
Single parent with one or more children	0.30***	0.03	0.24	0.29***	0.23*	0.33
	(0.06)	(0.14)	(0.16)	(0.11)	(0.12)	(0.28)
Patchwork family	0.47***	0.36**	0.21	0.59***	0.32**	-1.18
	(0.07)	(0.16)	(0.20)	(0.13)	(0.13)	(0.95)
Non-family shared household	0.48***	0.37***	0.46***	0.44***	0.16	0.75***
	(0.05)	(0.08)	(0.13)	(0.14)	(0.16)	(0.16)
Swiss	0.04	0.04	0.07	-0.01	0.01	-0.04
	(0.03)	(0.06)	(0.08)	(0.08)	(0.07)	(0.16)
Agglomeration	-0.08***					0.05
	(0.03)					(0.07)
Countryside	-0.09***		-0.08		0.02	-0.01
	(0.03)		(0.06)		(0.05)	(0.09)
Female	0.05**	0.06	0.03	0.16***	0.02	-0.01
	(0.02)	(0.04)	(0.05)	(0.05)	(0.04)	(0.07)

Owner	0.08***	0.06	0.08	0.04	0.08*	-0.01
	(0.03)	(0.08)	(0.06)	(0.06)	(0.05)	(0.07)
Constant	-1.27***	-1.79***	-1.49***	-0.67**	-1.67***	-0.06
	(0.12)	(0.24)	(0.32)	(0.30)	(0.32)	(0.50)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7451	1893	1525	1356	1700	921
Log-likelihood	-8898.6	-2213.2	-1737.2	-1629.1	-2097.9	-1046.2

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Poisson estimation

Table 31: Number of regio abos

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.09**	0.08	0.01	-0.06	0.25*	0.08
	(0.04)	(0.07)	(0.09)	(0.09)	(0.13)	(0.18)
Energy literacy squared	-0.01*	-0.01	0.00	0.00	-0.02*	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Injunctive norms	0.03	0.00	0.07	0.08*	0.07	-0.10
	(0.02)	(0.04)	(0.06)	(0.05)	(0.06)	(0.09)
Descriptive norms	0.01	0.03	-0.06	-0.04	-0.04	0.09
	(0.02)	(0.04)	(0.06)	(0.05)	(0.06)	(0.11)
Age (household)	-0.01***	0.01	0.00	-0.01**	-0.01	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	0.07***	0.10**	0.10**	0.08*	0.28***	0.14
	(0.02)	(0.04)	(0.05)	(0.04)	(0.04)	(0.12)
Education in years	-0.02**	-0.04**	-0.02	0.00	0.03	-0.02
	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)
Income 3'000-4'459	0.19*	0.11	0.73**	0.12	-0.13	0.48
	(0.11)	(0.19)	(0.29)	(0.21)	(0.27)	(0.36)
Income 4'500-5'999	0.14	0.18	0.27	-0.03	-0.35	0.71**
	(0.10)	(0.16)	(0.27)	(0.21)	(0.30)	(0.36)
Income 6'000-8'999	0.11	0.11	0.13	-0.01	-0.28	0.90**
	(0.10)	(0.16)	(0.26)	(0.19)	(0.24)	(0.35)
Income 9'000-12'000	0.16	0.22	-0.11	-0.06	-0.21	0.65
	(0.10)	(0.17)	(0.28)	(0.21)	(0.25)	(0.42)
Income 12'000 or more	0.29***	0.36**	0.16	-0.08	-0.25	-0.11
	(0.11)	(0.18)	(0.28)	(0.22)	(0.26)	(0.61)
Couple without children	0.20***	0.16	0.53***	0.24*	0.09	0.17
	(0.06)	(0.10)	(0.18)	(0.13)	(0.17)	(0.22)
Couple with children	0.49***	0.02	0.42*	0.48***	0.32*	0.50
	(0.08)	(0.16)	(0.21)	(0.17)	(0.19)	(0.46)
Single parent with one or more children	0.57***	0.38*	0.48	0.48***	0.31	0.49
	(0.10)	(0.20)	(0.33)	(0.16)	(0.26)	(0.63)
Patchwork family	0.52***	-0.05	0.95**	0.54**	0.09	1.23
	(0.12)	(0.25)	(0.37)	(0.22)	(0.26)	(0.88)
Non-family shared household	0.22**	0.25**	0.45	-0.34	-0.07	-0.19
	(0.10)	(0.13)	(0.28)	(0.28)	(0.39)	(0.57)
Swiss	-0.00	0.05	-0.00	-0.01	0.08	-0.35
	(0.07)	(0.10)	(0.16)	(0.15)	(0.18)	(0.41)
Agglomeration	-0.17***					-0.21
	(0.05)					(0.22)
Countryside	-0.41***		-0.40***		-0.21*	-0.65*
	(0.07)		(0.12)		(0.11)	(0.36)

Female	0.07*	0.13*	-0.03	0.06	0.05	-0.06
	(0.04)	(0.07)	(0.11)	(0.09)	(0.09)	(0.20)
Owner	-0.08	0.01	-0.07	-0.03	-0.21**	-0.68***
	(0.05)	(0.14)	(0.14)	(0.10)	(0.10)	(0.21)
Constant	-0.82***	-0.97**	-1.63**	-0.22	-2.40***	-2.11
	(0.25)	(0.42)	(0.63)	(0.57)	(0.73)	(1.44)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7451	1893	1525	1356	1700	921
Log-likelihood	-5476.4	-1574.4	-947.4	-1108.4	-1165.4	-432.6

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Poisson estimation

Table 32: Number of cars

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	-0.03***	-0.05***	-0.03***	-0.05***	-0.01**	-0.00
	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Injunctive norms	-0.06***	-0.09***	-0.02	-0.08**	-0.08***	-0.05*
	(0.01)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Descriptive norms	0.04***	0.05*	0.00	0.07**	0.05***	0.06*
	(0.01)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Age (household)	0.00**	0.01***	0.00	0.00	-0.00	-0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Household size	0.01	0.07**	-0.00	0.04	0.03**	-0.04
	(0.01)	(0.03)	(0.02)	(0.04)	(0.01)	(0.06)
Education in years	-0.03***	-0.06***	-0.03***	-0.04***	-0.01	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income 3'000-4'459	0.35***	0.47***	0.33**	0.17	0.26**	0.31**
	(0.07)	(0.18)	(0.16)	(0.20)	(0.12)	(0.13)
Income 4'500-5'999	0.50***	0.70***	0.49***	0.24	0.32***	0.54***
	(0.07)	(0.16)	(0.14)	(0.20)	(0.12)	(0.13)
Income 6'000-8'999	0.63***	0.89***	0.76***	0.41**	0.37***	0.58***
	(0.06)	(0.16)	(0.14)	(0.20)	(0.11)	(0.13)
Income 9'000-12'000	0.77***	1.06***	0.93***	0.51**	0.42***	0.72***
	(0.07)	(0.16)	(0.14)	(0.20)	(0.12)	(0.13)
Income 12'000 or more	0.90***	1.11***	1.01***	0.67***	0.59***	0.89***
	(0.07)	(0.17)	(0.14)	(0.21)	(0.12)	(0.16)
Couple without children	0.40***	0.32***	0.35***	0.63***	0.40***	0.26***
	(0.03)	(0.08)	(0.06)	(0.09)	(0.05)	(0.09)
Couple with children	0.48***	0.34***	0.37***	0.67***	0.42***	0.32*
	(0.04)	(0.11)	(0.07)	(0.12)	(0.06)	(0.17)
Single parent with one or more children	0.27***	0.24	0.22**	0.24*	0.20***	-0.01
	(0.05)	(0.15)	(0.11)	(0.13)	(0.07)	(0.26)
Patchwork family	0.56***	0.47***	0.46***	0.66***	0.54***	0.14
	(0.05)	(0.15)	(0.12)	(0.13)	(0.08)	(0.30)
Non-family shared household	0.21***	0.09	0.12	0.38**	0.27***	0.35***
	(0.06)	(0.11)	(0.12)	(0.16)	(0.10)	(0.12)
Swiss	0.06**	0.15**	0.09*	-0.17	0.07	0.12
	(0.03)	(0.07)	(0.05)	(0.11)	(0.05)	(0.13)
Agglomeration	0.32***					0.27***
	(0.02)					(0.05)
Countryside	0.48***		0.17***		0.17***	0.33***
	(0.02)		(0.03)		(0.03)	(0.06)

Female	-0.04**	-0.04	-0.02	-0.07	-0.02	-0.14***
	(0.02)	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)
Owner	0.17***	0.25***	0.11***	0.22***	0.17***	0.22***
	(0.02)	(0.07)	(0.04)	(0.06)	(0.03)	(0.05)
Constant	-0.85***	-1.02***	-0.64***	-0.45	-0.36	-0.32
	(0.11)	(0.33)	(0.22)	(0.34)	(0.23)	(0.39)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7451	1893	1525	1356	1700	921
Log-likelihood	-8385.0	-1802.6	-1877.2	-1412.7	-2167.1	-961.6

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Poisson estimation

Table 33: Number of motorbikes

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	-0.01	0.01	0.00	-0.01	-0.01	-0.03
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.06)
Injunctive norms	-0.11***	-0.17***	-0.10	0.01	-0.15**	-0.06
	(0.03)	(0.07)	(0.06)	(0.08)	(0.06)	(0.15)
Descriptive norms	0.06*	0.07	0.11*	-0.03	0.05	0.24
	(0.03)	(0.07)	(0.07)	(0.08)	(0.06)	(0.17)
Age (household)	-0.01***	-0.02	-0.01	-0.01	-0.01	-0.09***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Household size	0.04*	0.12***	0.06	-0.01	0.08**	0.02
	(0.02)	(0.03)	(0.07)	(0.07)	(0.04)	(0.25)
Education in years	-0.09***	-0.13***	-0.08***	-0.10***	-0.04	-0.07
	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)
Income 3'000-4'459	0.02	-0.12	0.62	1.12*	-0.34	-1.18
	(0.21)	(0.44)	(0.43)	(0.64)	(0.39)	(0.83)
Income 4'500-5'999	0.52***	0.62**	0.91**	1.14*	0.09	-0.20
	(0.19)	(0.31)	(0.37)	(0.61)	(0.36)	(0.66)
Income 6'000-8'999	0.70***	0.88***	0.76**	1.75***	0.04	0.38
	(0.18)	(0.29)	(0.35)	(0.59)	(0.37)	(0.66)
Income 9'000-12'000	0.82***	0.97***	0.97***	1.94***	0.05	-0.11
	(0.19)	(0.30)	(0.36)	(0.61)	(0.39)	(0.71)
Income 12'000 or more	0.97***	1.26***	0.90**	2.15***	0.07	0.14
	(0.19)	(0.32)	(0.37)	(0.61)	(0.38)	(0.81)
Couple without children	0.49***	0.18	0.75***	0.80***	0.51**	0.60
	(0.10)	(0.18)	(0.23)	(0.23)	(0.21)	(0.56)
Couple with children	0.46***	-0.03	0.48	0.54*	0.37	0.70
	(0.12)	(0.23)	(0.33)	(0.30)	(0.23)	(0.87)
Single parent with one or more children	0.14	-0.42	-1.45*	0.10	0.28	0.30
	(0.16)	(0.44)	(0.76)	(0.32)	(0.26)	(1.17)
Patchwork family	0.79***	0.67**	0.93**	0.78**	0.63**	0.70
	(0.16)	(0.33)	(0.44)	(0.37)	(0.26)	(0.97)
Non-family shared household	0.38***	-0.13	0.88***	0.86**	-0.63	1.41**
	(0.14)	(0.22)	(0.30)	(0.40)	(0.45)	(0.62)
Swiss	0.43***	0.46**	0.41*	0.29	0.49**	0.44
	(0.12)	(0.19)	(0.22)	(0.33)	(0.23)	(0.72)
Agglomeration	0.09					0.23
	(0.07)					(0.29)
Countryside	0.10		-0.24*		0.17	0.15
	(0.08)		(0.13)		(0.12)	(0.38)

Female	-0.13**	-0.09	-0.05	-0.15	-0.19	-0.72**
	(0.06)	(0.12)	(0.12)	(0.14)	(0.12)	(0.36)
Owner	0.23***	0.36*	0.40***	0.01	0.08	0.36
	(0.07)	(0.20)	(0.14)	(0.16)	(0.12)	(0.26)
Constant	-1.34***	-0.81	-1.84**	-2.00**	-1.25	2.98*
	(0.34)	(0.71)	(0.73)	(0.93)	(0.81)	(1.80)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7451	1893	1525	1356	1700	921
Log-likelihood	-4068.0	-885.6	-868.8	-751.1	-1142.3	-212.2

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Poisson estimation

Table 34: Number of bikes

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.04***	0.04***	0.02**	0.04***	0.02*	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Injunctive norms	0.06***	0.04*	0.07***	0.08***	0.08***	0.10**
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.05)
Descriptive norms	-0.05***	-0.05**	-0.02	-0.09***	-0.07***	-0.01
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.05)
Age (household)	-0.01***	0.01***	0.01***	-0.02***	-0.02***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Household size	0.05***	0.10***	0.13***	0.13***	0.16***	0.05
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.07)
Education in years	0.03***	0.03***	0.02*	0.04***	0.04***	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Income 3'000-4'459	-0.09	-0.08	-0.27**	0.18	-0.02	-0.23
	(0.06)	(0.10)	(0.13)	(0.16)	(0.13)	(0.15)
Income 4'500-5'999	0.02	0.02	-0.12	0.26*	0.05	-0.15
	(0.05)	(0.08)	(0.10)	(0.15)	(0.12)	(0.15)
Income 6'000-8'999	0.09**	0.10	-0.09	0.27*	0.10	-0.03
	(0.05)	(0.08)	(0.09)	(0.14)	(0.12)	(0.15)
Income 9'000-12'000	0.16***	0.10	0.02	0.26*	0.17	-0.08
	(0.05)	(0.08)	(0.10)	(0.14)	(0.12)	(0.17)
Income 12'000 or more	0.22***	0.22***	-0.05	0.23	0.14	0.07
	(0.05)	(0.09)	(0.10)	(0.15)	(0.13)	(0.21)
Couple without children	0.46***	0.58***	0.25***	0.47***	0.39***	0.42***
	(0.04)	(0.06)	(0.08)	(0.08)	(0.08)	(0.14)
Couple with children	0.92***	0.63***	0.50***	0.74***	0.64***	0.80***
	(0.06)	(0.10)	(0.10)	(0.09)	(0.10)	(0.26)
Single parent with one or more children	0.53***	0.31**	0.19	0.31***	0.36***	0.58**
	(0.06)	(0.13)	(0.14)	(0.10)	(0.10)	(0.25)
Patchwork family	0.77***	0.61***	0.40***	0.47***	0.51***	0.20
	(0.07)	(0.16)	(0.15)	(0.13)	(0.11)	(0.35)
Non-family shared household	0.54***	0.65***	0.38***	0.15	-0.14	0.50**
	(0.06)	(0.08)	(0.12)	(0.13)	(0.22)	(0.20)
Swiss	0.09***	0.14**	0.09	-0.00	0.12*	0.22
	(0.03)	(0.06)	(0.06)	(0.09)	(0.07)	(0.26)
Agglomeration	-0.03					-0.01
	(0.02)					(0.09)
Countryside	-0.02		0.01		0.02	-0.12
	(0.03)		(0.04)		(0.03)	(0.11)

Female	0.03*	0.04	0.02	0.03	0.05	-0.19**
	(0.02)	(0.04)	(0.04)	(0.05)	(0.03)	(0.09)
Owner	0.19***	0.10	0.19***	0.17***	0.11***	0.19**
	(0.02)	(0.07)	(0.04)	(0.05)	(0.04)	(0.09)
Constant	-0.57***	-1.41***	-0.87***	-0.48	-0.43*	0.42
	(0.11)	(0.22)	(0.24)	(0.29)	(0.23)	(0.63)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7451	1893	1525	1356	1700	921
Log-likelihood	-11697.6	-2905.0	-2384.8	-2105.2	-2791.1	-1120.1

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Poisson estimation

Table 35: Number of E-bikes

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.06***	0.11**	0.09**	0.15***	0.00	0.03
	(0.02)	(0.04)	(0.04)	(0.05)	(0.03)	(0.05)
Injunctive norms	0.04	0.06	0.03	0.02	0.03	0.15
	(0.03)	(0.08)	(0.09)	(0.07)	(0.06)	(0.10)
Descriptive norms	-0.01	-0.05	-0.07	0.12	0.01	-0.03
	(0.04)	(0.08)	(0.08)	(0.08)	(0.06)	(0.11)
Age (household)	0.01***	0.01	0.02	-0.00	-0.00	-0.04***
	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	0.04*	0.15***	0.08	-0.04	0.11**	0.03
	(0.02)	(0.05)	(0.07)	(0.07)	(0.04)	(0.18)
Education in years	-0.01	0.01	0.01	-0.05	0.02	-0.01
	(0.02)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
Income 3'000-4'459	0.10	0.66	-0.21	0.69	-0.27	-0.24
	(0.21)	(0.52)	(0.58)	(0.59)	(0.39)	(0.35)
Income 4'500-5'999	0.31	0.91**	0.67	0.56	0.09	-0.30
	(0.19)	(0.45)	(0.47)	(0.58)	(0.35)	(0.35)
Income 6'000-8'999	0.40**	0.72	0.62	0.85	0.10	0.14
	(0.18)	(0.45)	(0.44)	(0.56)	(0.34)	(0.33)
Income 9'000-12'000	0.52***	0.92**	0.85*	1.01*	0.19	0.04
	(0.19)	(0.46)	(0.46)	(0.58)	(0.35)	(0.38)
Income 12'000 or more	0.52***	0.77	0.88*	0.96	0.25	-0.08
	(0.19)	(0.48)	(0.47)	(0.59)	(0.36)	(0.51)
Couple without children	0.46***	0.44*	-0.02	0.45**	0.50***	0.68**
	(0.10)	(0.25)	(0.27)	(0.22)	(0.18)	(0.30)
Couple with children	0.67***	1.09***	0.31	0.71**	0.10	0.45
	(0.12)	(0.28)	(0.34)	(0.27)	(0.23)	(0.59)
Single parent with one or more children	0.12	-0.27	-0.64	0.04	0.04	-0.73
	(0.18)	(0.57)	(0.56)	(0.32)	(0.28)	(0.98)
Patchwork family	0.76***	0.42	0.03	0.69*	0.51*	0.16
	(0.19)	(0.56)	(0.55)	(0.38)	(0.31)	(0.87)
Non-family shared household	0.09	0.22	-0.67	0.45	-0.72	0.87**
	(0.18)	(0.32)	(0.47)	(0.41)	(0.45)	(0.44)
Swiss	0.43***	0.36	0.25	0.52	0.56**	0.33
	(0.14)	(0.28)	(0.28)	(0.41)	(0.24)	(0.46)
Agglomeration	0.16**					0.47**
	(0.08)					(0.20)

Countryside	0.24***		0.14		0.14	0.25
	(0.08)		(0.16)		(0.11)	(0.25)
Female	0.18***	0.42**	0.10	0.04	0.22**	0.22
	(0.06)	(0.16)	(0.16)	(0.14)	(0.11)	(0.18)
Owner	0.51***	0.30	0.44***	0.34**	0.47***	0.45**
	(0.07)	(0.22)	(0.16)	(0.14)	(0.13)	(0.19)
Constant	-4.71***	-6.31***	-5.25***	-4.51***	-3.30***	-1.09
	(0.39)	(1.02)	(0.98)	(0.96)	(0.78)	(1.30)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7451	1893	1525	1356	1700	921
Log-likelihood	-3720.0	-604.4	-652.2	-672.0	-1128.8	-489.3

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Poisson estimation

Table 36: Electric car ownership

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.05***	0.11**	0.07	0.07	0.04	0.04
	(0.02)	(0.05)	(0.04)	(0.06)	(0.03)	(0.06)
Injunctive norms	0.02	-0.14	0.06	0.34***	-0.05	0.02
	(0.04)	(0.11)	(0.09)	(0.13)	(0.07)	(0.11)
Descriptive norms	-0.06	-0.02	-0.13	-0.04	-0.03	-0.10
	(0.04)	(0.09)	(0.11)	(0.15)	(0.08)	(0.12)
Age (household)	0.01**	0.03**	0.03**	0.01	0.01	-0.02
	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Household size	-0.03	0.02	-0.14	-0.11	0.14**	-0.47*
	(0.04)	(0.09)	(0.12)	(0.14)	(0.06)	(0.24)
Education in years	0.04**	-0.02	0.09**	0.03	0.10***	0.01
	(0.02)	(0.05)	(0.04)	(0.05)	(0.03)	(0.05)
Income 3'000-4'459	-0.20	-0.19			-0.67	0.10
	(0.24)	(0.60)			(0.42)	(0.50)
Income 4'500-5'999	0.04	0.29	-0.52	0.04	-0.53	0.35
	(0.21)	(0.50)	(0.55)	(0.30)	(0.38)	(0.47)
Income 6'000-8'999	-0.05	0.13	-0.07	-0.39	-0.53	0.25
	(0.20)	(0.48)	(0.42)	(0.30)	(0.35)	(0.53)
Income 9'000-12'000	-0.09	-0.16	-0.35	-0.49*	-0.68*	0.63
	(0.21)	(0.50)	(0.44)	(0.28)	(0.36)	(0.55)
Income 12'000 or more	0.14	-0.20	0.16		-0.52	0.29
	(0.21)	(0.51)	(0.45)		(0.37)	(0.62)
Couple without children	-0.07	0.43	0.51*	-0.19	-0.24	-0.13
	(0.11)	(0.28)	(0.30)	(0.30)	(0.21)	(0.33)
Couple with children	-0.08	-0.02	0.26	0.01	-0.51*	0.86*
	(0.16)	(0.41)	(0.39)	(0.42)	(0.27)	(0.52)
Single parent with one or more children	-0.20	0.18	0.20		-0.43	
	(0.22)	(0.48)	(0.55)		(0.38)	
Patchwork family	-0.07	0.51	0.33	0.04	-0.34	
	(0.22)	(0.66)	(0.63)	(0.49)	(0.39)	
Non-family shared household	0.24	0.59*		-0.12	0.30	0.73
	(0.17)	(0.32)		(0.60)	(0.34)	(0.48)
Swiss	0.21	0.30	-0.03	-0.25	0.45	
	(0.13)	(0.34)	(0.25)	(0.25)	(0.31)	
Agglomeration	-0.05					0.23
	(0.08)					(0.20)

Countryside	-0.10		0.00		-0.02	-0.14
	(0.09)		(0.18)		(0.15)	(0.28)
Female	-0.10	-0.28*	-0.20	-0.14	-0.04	0.05
	(0.07)	(0.16)	(0.17)	(0.21)	(0.13)	(0.23)
Owner	0.22***	0.25	0.38**	0.42*	0.27*	-0.13
	(0.08)	(0.23)	(0.19)	(0.22)	(0.15)	(0.19)
Constant	-3.05***	-3.15***	-4.29***	-3.71**	-4.15***	-0.18
	(0.43)	(1.04)	(0.99)	(1.53)	(0.94)	(1.91)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5114	752	952	545	1342	547
Log-likelihood	-779.9	-118.1	-137.0	-98.4	-215.2	-108.6

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit estimation.

Table 37: Mode of transport - work

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Private car						
Energy literacy	-0.07***	-0.08**	-0.06*	-0.09**	-0.09***	-0.27
	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(.)
Injunctive norms	-0.16***	-0.14*	-0.09	-0.28***	-0.20***	-0.13
	(0.04)	(0.07)	(0.07)	(0.09)	(0.08)	(.)
Descriptive norms	0.09**	-0.03	0.12	0.07	0.22***	0.40
	(0.04)	(0.08)	(0.07)	(0.09)	(0.08)	(.)
Age	0.02***	0.06***	0.08***	0.01	0.00	0.00
	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(.)
Household size	-0.05	0.07	-0.17	0.08	-0.08	0.19
	(0.05)	(0.09)	(0.15)	(0.13)	(0.08)	(.)
Education in years	-0.09***	-0.14***	-0.13***	-0.05	-0.15***	-0.18
	(0.02)	(0.04)	(0.03)	(0.04)	(0.04)	(.)
Income 3'000-4'459	0.73***	1.45***	0.46	0.27	1.00**	-0.45
	(0.18)	(0.45)	(0.40)	(0.48)	(0.41)	(.)
Income 4'500-5'999	0.85***	1.12***	1.17***	0.26	0.95**	0.49
	(0.17)	(0.42)	(0.36)	(0.45)	(0.38)	(.)
Income 6'000-8'999	0.97***	1.49***	1.22***	0.47	0.63*	0.17
	(0.16)	(0.42)	(0.36)	(0.42)	(0.35)	(.)
Income 9'000-12'000	1.03***	1.43***	1.73***	0.21	0.42	-0.56
	(0.17)	(0.43)	(0.38)	(0.45)	(0.37)	(.)
Income 12'000 or more	1.03***	1.17***	1.51***	0.22	0.77**	0.10
	(0.17)	(0.45)	(0.39)	(0.46)	(0.38)	(.)
Couple without children	0.01	0.08	-0.11	0.21	0.10	-0.49
	(0.10)	(0.22)	(0.25)	(0.25)	(0.21)	(.)
Couple with children	0.06	0.01	-0.08	0.15	0.35	-1.05
	(0.16)	(0.34)	(0.45)	(0.41)	(0.30)	(.)
Single parent with one or more children	0.01	-0.99**	-0.64	0.37	0.88***	-0.37
	(0.17)	(0.44)	(0.41)	(0.37)	(0.34)	(.)
Patchwork family	0.37*	0.28	0.28	0.18	0.89**	21.88
	(0.21)	(0.47)	(0.60)	(0.45)	(0.41)	(.)
Non-family shared household	-0.30*	-0.44	-0.32	-0.01	-0.15	-1.06
	(0.17)	(0.30)	(0.41)	(0.57)	(0.45)	(.)
Swiss	0.14	0.15	0.24	-0.21	0.10	2.33
	(0.10)	(0.19)	(0.20)	(0.26)	(0.24)	(.)

Agglomeration	0.77***					0.42
	(0.08)					(.)
Countryside	1.34***		0.64***		0.45***	2.16
	(0.09)		(0.14)		(0.14)	(.)
Female	-0.24***	-0.43***	-0.21	-0.30*	-0.03	-0.89
	(0.07)	(0.14)	(0.13)	(0.17)	(0.14)	(.)
Owner	0.11	0.35	-0.18	0.36*	0.28**	1.08
	(0.08)	(0.25)	(0.17)	(0.19)	(0.14)	(.)
Constant	-0.65*	-1.51*	-1.72**	0.32	1.59*	0.13
	(0.35)	(0.83)	(0.76)	(1.06)	(0.93)	(.)
Soft mobility						
Energy literacy	0.04**	0.04	0.08*	0.10**	-0.09*	0.16
	(0.02)	(0.03)	(0.05)	(0.04)	(0.05)	(.)
Injunctive norms	-0.01	-0.01	-0.19*	-0.03	0.09	0.59
	(0.04)	(0.07)	(0.10)	(0.08)	(0.12)	(.)
Descriptive norms	-0.06	-0.11	-0.02	-0.10	0.04	-0.13
	(0.04)	(0.07)	(0.10)	(0.09)	(0.11)	(.)
Age	0.01***	0.05***	0.04**	-0.00	0.00	-0.11
	(0.00)	(0.01)	(0.02)	(0.01)	(0.02)	(.)
Household size	0.06	0.16**	0.04	0.03	-0.01	-31.04
	(0.04)	(0.07)	(0.08)	(0.12)	(0.12)	(.)
Education in years	0.01	0.09**	-0.03	0.01	-0.08	-0.08
	(0.02)	(0.04)	(0.05)	(0.04)	(0.05)	(.)
Income 3'000-4'459	-0.20	-0.26	-1.33***	-0.11	0.68	0.74
	(0.17)	(0.27)	(0.43)	(0.38)	(0.55)	(.)
Income 4'500-5'999	-0.21	-0.52**	-0.62*	-0.03	0.46	-0.43
	(0.16)	(0.24)	(0.37)	(0.37)	(0.53)	(.)
Income 6'000-8'999	-0.06	-0.07	-0.77**	-0.02	0.05	-0.55
	(0.15)	(0.23)	(0.35)	(0.35)	(0.50)	(.)
Income 9'000-12'000	-0.18	-0.20	-0.72*	-0.16	-0.09	-1.83
	(0.16)	(0.24)	(0.39)	(0.37)	(0.51)	(.)
Income 12'000 or more	-0.46***	-0.66**	-1.19***	-0.50	-0.20	0.68
	(0.17)	(0.27)	(0.44)	(0.39)	(0.54)	(.)
Couple without children	-0.05	-0.22	-0.16	-0.02	0.32	31.35
	(0.11)	(0.18)	(0.29)	(0.25)	(0.31)	(.)
Couple with children	-0.10	-0.71**	-0.53	0.35	0.71	30.56
	(0.16)	(0.28)	(0.35)	(0.38)	(0.46)	(.)
Single parent with one or more children	-0.36*	-0.87**	-0.75	-0.20	0.51	32.95
	(0.19)	(0.38)	(0.58)	(0.36)	(0.50)	(.)
Patchwork family	-0.23	-1.28*	-1.17	0.12	0.74	100.88
	(0.26)	(0.67)	(0.89)	(0.46)	(0.64)	(.)
Non-family shared household	0.11	-0.18	-0.19	0.86**	0.35	31.85
	(0.16)	(0.23)	(0.43)	(0.42)	(0.59)	(.)
Swiss	0.03	0.05	-0.25	-0.22	0.41	1.60
	(0.11)	(0.17)	(0.28)	(0.25)	(0.39)	(.)
Agglomeration	-0.47***					0.42
	(0.10)					(.)
Countryside	-0.37***		0.11		0.04	-0.99
	(0.11)		(0.20)		(0.20)	(.)
Female	0.17**	0.03	-0.37**	0.54***	0.57***	-0.17
	(0.08)	(0.12)	(0.19)	(0.16)	(0.20)	(.)
Owner	-0.03	-0.48*	0.09	0.06	0.11	0.45
	(0.10)	(0.27)	(0.24)	(0.18)	(0.20)	(.)

Constant	-1.85***	-3.67***	-1.43	-1.29	-1.43	34.05
	(0.39)	(0.75)	(1.14)	(0.96)	(1.36)	(.)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6140	1809	1417	1181	1482	200
Log-likelihood	-5811.0	-1634.3	-1251.6	-1150.2	-1305.5	-149.6

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Multinomial logit estimation

Table 38: Mode of transport - leisure

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Private car						
Energy literacy	-0.09***	-0.14***	-0.08**	-0.10**	-0.11***	-0.02
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Injunctive norms	-0.22***	-0.22***	-0.17**	-0.13*	-0.28***	-0.36***
	(0.03)	(0.07)	(0.09)	(0.08)	(0.09)	(0.10)
Descriptive norms	0.12***	0.07	0.11	0.16*	0.14*	0.23**
	(0.04)	(0.07)	(0.08)	(0.08)	(0.08)	(0.11)
Age	-0.00	0.01	0.06***	0.00	-0.03***	-0.04**
	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Household size	-0.05	-0.11	-0.09	0.02	-0.07	0.21
	(0.04)	(0.09)	(0.11)	(0.11)	(0.10)	(0.18)
Education in years	-0.03**	-0.07**	-0.05	-0.05	-0.05	-0.06
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Income 3'000-4'459	0.77***	0.94***	0.86**	0.37	1.07***	0.56
	(0.15)	(0.33)	(0.37)	(0.37)	(0.36)	(0.36)
Income 4'500-5'999	0.79***	0.88***	1.08***	0.20	0.95***	0.57
	(0.14)	(0.31)	(0.33)	(0.34)	(0.35)	(0.36)
Income 6'000-8'999	1.08***	1.18***	1.32***	0.71**	1.12***	0.77**
	(0.14)	(0.30)	(0.33)	(0.32)	(0.33)	(0.37)
Income 9'000-12'000	1.30***	1.48***	1.66***	0.77**	1.29***	0.88**
	(0.15)	(0.32)	(0.36)	(0.35)	(0.35)	(0.42)
Income 12'000 or more	1.40***	1.36***	1.88***	0.59	1.49***	1.97***
	(0.16)	(0.34)	(0.39)	(0.36)	(0.37)	(0.55)
Couple without children	0.36***	0.33*	0.46*	0.83***	0.36	-0.08
	(0.09)	(0.19)	(0.24)	(0.22)	(0.23)	(0.29)
Couple with children	0.71***	0.84***	0.67*	1.00***	0.48	-0.38
	(0.14)	(0.31)	(0.37)	(0.37)	(0.36)	(0.56)
Single parent with one or more children	0.10	-0.12	-0.67	0.35	0.28	0.62
	(0.16)	(0.37)	(0.41)	(0.34)	(0.35)	(0.80)
Patchwork family	0.75***	0.85*	-0.06	1.10***	0.88*	-0.29
	(0.21)	(0.46)	(0.55)	(0.42)	(0.47)	(1.35)
Non-family shared household	-0.27*	-0.38	-0.64*	0.72*	-0.06	-0.06
	(0.15)	(0.28)	(0.35)	(0.39)	(0.41)	(0.48)
Swiss	0.08	-0.04	0.13	-0.28	0.18	0.95**
	(0.10)	(0.17)	(0.23)	(0.23)	(0.28)	(0.43)
Agglomeration	0.85***					0.67***
	(0.07)					(0.19)
Countryside	1.35***		0.68***		0.44***	0.87***
	(0.09)		(0.15)		(0.16)	(0.24)
Female	-0.33***	-0.31**	-0.38**	-0.40***	-0.22	-0.49***
	(0.06)	(0.12)	(0.15)	(0.14)	(0.15)	(0.18)

Owner	0.32***	1.07***	0.15	0.36**	0.46***	0.27
	(0.08)	(0.28)	(0.20)	(0.17)	(0.16)	(0.18)
Constant	-0.10	0.31	-1.47*	-0.01	3.18***	1.59
	(0.33)	(0.76)	(0.84)	(0.89)	(1.03)	(1.56)
Soft mobility						
Energy literacy	0.03	0.03	0.04	0.06	-0.08	0.13**
	(0.02)	(0.03)	(0.05)	(0.04)	(0.05)	(0.07)
Injunctive norms	-0.01	0.04	-0.06	0.13	-0.10	-0.23
	(0.04)	(0.07)	(0.11)	(0.09)	(0.11)	(0.15)
Descriptive norms	0.01	-0.02	0.11	-0.12	0.06	0.24
	(0.04)	(0.07)	(0.11)	(0.09)	(0.11)	(0.17)
Age	-0.01***	0.01	0.04*	-0.02	-0.02	-0.07***
	(0.00)	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)
Household size	0.04	-0.01	0.15*	0.02	-0.07	0.37*
	(0.04)	(0.07)	(0.08)	(0.12)	(0.12)	(0.21)
Education in years	0.05***	0.06	0.02	0.09**	0.01	-0.12*
	(0.02)	(0.04)	(0.05)	(0.04)	(0.05)	(0.07)
Income 3'000-4'459	-0.02	-0.20	-0.39	0.31	0.80*	-0.55
	(0.15)	(0.27)	(0.42)	(0.37)	(0.45)	(0.39)
Income 4'500-5'999	-0.14	-0.20	-0.22	0.07	0.48	-0.97**
	(0.14)	(0.23)	(0.35)	(0.35)	(0.44)	(0.40)
Income 6'000-8'999	-0.01	0.08	-0.48	0.02	0.47	-0.49
	(0.13)	(0.22)	(0.34)	(0.34)	(0.41)	(0.40)
Income 9'000-12'000	0.08	-0.09	-0.10	-0.10	0.85**	-0.10
	(0.15)	(0.24)	(0.37)	(0.37)	(0.43)	(0.47)
Income 12'000 or more	-0.20	-0.35	-0.47	-0.54	0.46	0.56
	(0.16)	(0.27)	(0.44)	(0.39)	(0.45)	(0.65)
Couple without children	0.14	0.34*	-0.12	0.09	0.38	-0.20
	(0.10)	(0.18)	(0.29)	(0.26)	(0.29)	(0.37)
Couple with children	0.39**	0.43	0.07	0.56	0.63	-1.16
	(0.15)	(0.27)	(0.34)	(0.41)	(0.44)	(0.79)
Single parent with one or more children	-0.07	-0.27	-1.05**	-0.14	0.36	1.12
	(0.18)	(0.37)	(0.52)	(0.36)	(0.45)	(0.82)
Patchwork family	0.22	-0.07	-1.08	0.61	0.76	-14.62***
	(0.25)	(0.58)	(0.69)	(0.48)	(0.59)	(0.92)
Non-family shared household	0.04	0.33	-0.77*	0.06	0.00	0.25
	(0.15)	(0.23)	(0.44)	(0.49)	(0.59)	(0.56)
Swiss	0.11	0.26	-0.25	0.12	-0.07	2.03*
	(0.12)	(0.18)	(0.28)	(0.27)	(0.35)	(1.09)
Agglomeration	-0.03					0.37
	(0.09)					(0.26)
Countryside	0.03		0.09		0.17	0.11
	(0.11)		(0.21)		(0.21)	(0.34)
Female	0.08	0.09	-0.12	0.03	0.46**	-0.41
	(0.07)	(0.13)	(0.20)	(0.17)	(0.20)	(0.25)
Owner	0.37***	0.91***	0.43*	0.36*	0.44**	0.47*
	(0.09)	(0.29)	(0.25)	(0.19)	(0.20)	(0.28)
Constant	-1.62***	-2.67***	-2.50**	-2.09**	-0.29	2.16
	(0.37)	(0.74)	(1.11)	(1.02)	(1.33)	(2.34)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7262	1832	1489	1309	1664	914
Log-likelihood	-6676.1	-1812.2	-1182.1	-1271.2	-1298.5	-797.5

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Multinomial logit estimation

Table 39: Mode of transport - grocery shopping

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Private car						
Energy literacy	-0.02	-0.04	-0.12	-0.07	0.14	-0.04
	(0.04)	(0.06)	(0.10)	(0.09)	(.)	(0.12)
Injunctive norms	-0.21***	-0.27**	-0.19	-0.34**	-0.18	-0.13
	(0.08)	(0.13)	(0.20)	(0.17)	(.)	(0.27)
Descriptive norms	0.08	0.35**	-0.21	0.07	0.12	-0.26
	(0.08)	(0.15)	(0.19)	(0.19)	(.)	(0.34)
Age	-0.00	0.06*	-0.00	0.02	-0.00	-0.02
	(0.01)	(0.03)	(0.04)	(0.03)	(.)	(0.04)
Household size	-0.08	-0.17*	0.04	0.46**	0.16	-0.07
	(0.09)	(0.10)	(0.26)	(0.22)	(.)	(0.42)
Education in years	0.04	-0.08	-0.02	0.05	0.09	0.04
	(0.04)	(0.08)	(0.10)	(0.08)	(.)	(0.12)
Income 3'000-4'459	0.78***	1.77***	0.24	-0.77	1.68	1.76**
	(0.28)	(0.62)	(0.89)	(0.57)	(.)	(0.79)
Income 4'500-5'999	0.76***	1.87***	-0.24	0.03	0.99	1.42*
	(0.25)	(0.59)	(0.71)	(0.57)	(.)	(0.77)
Income 6'000-8'999	1.15***	2.47***	0.75	0.20	0.79	1.61**
	(0.25)	(0.60)	(0.74)	(0.55)	(.)	(0.72)
Income 9'000-12'000	1.56***	2.61***	2.39**	-0.05	1.83	2.33**
	(0.29)	(0.62)	(0.96)	(0.63)	(.)	(1.13)
Income 12'000 or more	1.90***	3.24***	1.70*	0.73	1.02	17.18***
	(0.33)	(0.72)	(0.98)	(0.71)	(.)	(0.97)
Couple without children	0.23	0.06	-0.73	0.12	-0.21	-0.12
	(0.21)	(0.36)	(0.59)	(0.52)	(.)	(0.67)
Couple with children	0.57*	0.38	-0.81	0.54	1.09	0.60
	(0.34)	(0.49)	(0.91)	(0.75)	(.)	(1.48)
Single parent with one or more children	-0.15	-0.45	-0.61	-0.16	-0.91	15.73***
	(0.31)	(0.61)	(1.19)	(0.62)	(.)	(2.34)
Patchwork family	0.09	0.15	-2.10	0.70	0.14	-0.90
	(0.46)	(0.86)	(1.30)	(0.94)	(.)	(1.93)
Non-family shared household	-0.60*	-0.68	-2.30**	0.17	-1.01	-0.66
	(0.32)	(0.50)	(0.89)	(0.98)	(.)	(1.00)
Swiss	-0.17	-0.11	-0.04	-1.26*	0.72	0.44
	(0.23)	(0.36)	(0.52)	(0.70)	(.)	(0.96)
Agglomeration	1.23***					1.20**
	(0.18)					(0.53)
Countryside	2.02***		1.02**		0.25	2.17***
	(0.24)		(0.42)		(.)	(0.73)
Female	-0.09	-0.37	-0.53	0.40	0.74	-0.27
	(0.15)	(0.26)	(0.40)	(0.32)	(.)	(0.57)
Owner	0.62***	-0.17	0.26	0.79**	1.01	1.72***
	(0.21)	(0.46)	(0.52)	(0.38)	(.)	(0.56)
Constant	-0.53	-2.26	4.43**	0.57	-2.23	0.80
	(0.70)	(1.43)	(2.19)	(1.86)	(.)	(3.70)
Soft mobility						
Energy literacy	0.04	0.05	-0.10	0.08	0.16	0.05
	(0.03)	(0.05)	(0.10)	(0.08)	(.)	(0.11)
Injunctive norms	-0.06	-0.05	-0.16	-0.18	0.00	0.22
	(0.07)	(0.11)	(0.19)	(0.15)	(.)	(0.23)

Descriptive norms	0.04	0.30**	-0.22	0.08	0.01	-0.20
	(0.08)	(0.13)	(0.18)	(0.18)	(.)	(0.31)
Age	-0.01	0.10***	-0.03	-0.02	0.01	-0.06
	(0.00)	(0.03)	(0.04)	(0.02)	(.)	(0.04)
Household size	-0.07	-0.07	0.11	0.36*	0.15	0.02
	(0.09)	(0.09)	(0.26)	(0.22)	(.)	(0.39)
Education in years	0.09**	0.05	0.03	0.15*	0.13	0.02
	(0.03)	(0.07)	(0.10)	(0.08)	(.)	(0.11)
Income 3'000-4'459	0.45*	0.35	0.27	0.02	1.43	0.54
	(0.24)	(0.43)	(0.87)	(0.44)	(.)	(0.66)
Income 4'500-5'999	0.38*	0.23	-0.28	0.61	0.75	0.62
	(0.22)	(0.40)	(0.68)	(0.48)	(.)	(0.63)
Income 6'000-8'999	0.51**	0.72*	0.42	0.37	0.28	0.48
	(0.22)	(0.41)	(0.72)	(0.46)	(.)	(0.59)
Income 9'000-12'000	0.69***	0.66	1.66*	-0.07	1.31	1.45
	(0.26)	(0.43)	(0.94)	(0.54)	(.)	(1.04)
Income 12'000 or more	1.04***	1.53***	1.10	0.69	0.16	15.90***
	(0.30)	(0.53)	(0.95)	(0.62)	(.)	(0.86)
Couple without children	0.00	-0.20	-1.07*	-0.07	-0.50	-0.41
	(0.20)	(0.32)	(0.59)	(0.47)	(.)	(0.62)
Couple with children	0.38	-0.33	-0.91	0.05	1.11	0.81
	(0.32)	(0.45)	(0.89)	(0.70)	(.)	(1.41)
Single parent with one or more children	-0.47	-1.01*	-0.58	-0.67	-1.22	15.15***
	(0.29)	(0.54)	(1.19)	(0.57)	(.)	(2.16)
Patchwork family	-0.19	-0.41	-2.09*	0.23	-0.32	-1.74
	(0.44)	(0.77)	(1.27)	(0.90)	(.)	(1.82)
Non-family shared household	-0.15	-0.12	-1.77**	0.38	-1.03	-0.97
	(0.28)	(0.39)	(0.86)	(0.88)	(.)	(0.91)
Swiss	-0.19	0.10	-0.04	-1.28*	0.79	0.78
	(0.22)	(0.32)	(0.51)	(0.67)	(.)	(1.02)
Agglomeration	0.30*					0.57
	(0.17)					(0.50)
Countryside	0.84***		0.75*		0.10	1.10
	(0.24)		(0.41)		(.)	(0.70)
Female	-0.00	-0.14	-0.51	0.44	0.71	0.21
	(0.14)	(0.23)	(0.39)	(0.29)	(.)	(0.53)
Owner	0.18	-1.20***	-0.21	0.23	0.82	1.03**
	(0.20)	(0.44)	(0.52)	(0.35)	(.)	(0.52)
Constant	0.80	-2.94**	5.49**	1.55	-2.69	4.20
	(0.65)	(1.27)	(2.18)	(1.68)	(.)	(3.45)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5420	1527	1222	930	1174	515
Log-likelihood	-3825.5	-875.5	-893.0	-621.1	-796.8	-342.6

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Multinomial logit estimation

Table 40: Driven distance by car in km - self-assessed

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	-0.02**	-0.02	-0.00	-0.02	-0.02	-0.01
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Injunctive norms	-0.05***	-0.01	-0.04	-0.09**	-0.07**	-0.07
	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.06)
Descriptive norms	0.05***	0.00	0.10***	0.09*	0.05	0.04
	(0.02)	(0.04)	(0.04)	(0.05)	(0.03)	(0.06)
Age (household)	-0.01***	-0.01	-0.01	-0.00	-0.01**	-0.02**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Household size	-0.04**	-0.05	-0.03	-0.02	-0.02	-0.27**
	(0.02)	(0.04)	(0.05)	(0.06)	(0.03)	(0.11)
Education in years	0.01*	-0.00	-0.01	0.03	0.03**	0.00
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Income 3'000-4'459	0.20*	0.01	0.06	0.22	0.31	0.60***
	(0.10)	(0.24)	(0.25)	(0.26)	(0.21)	(0.21)
Income 4'500-5'999	0.31***	-0.03	0.43*	0.43*	0.30	0.72***
	(0.10)	(0.22)	(0.23)	(0.22)	(0.20)	(0.21)
Income 6'000-8'999	0.44***	0.15	0.48**	0.60***	0.43**	0.76***
	(0.09)	(0.21)	(0.22)	(0.22)	(0.19)	(0.21)
Income 9'000-12'000	0.49***	0.29	0.57**	0.53**	0.43**	0.85***
	(0.10)	(0.21)	(0.22)	(0.23)	(0.20)	(0.23)
Income 12'000 or more	0.57***	0.20	0.52**	0.67***	0.68***	1.07***
	(0.10)	(0.22)	(0.23)	(0.23)	(0.20)	(0.27)
Couple without children	0.05	0.15	-0.02	0.07	-0.04	0.17
	(0.05)	(0.11)	(0.10)	(0.13)	(0.10)	(0.17)
Couple with children	0.13*	0.20	0.10	0.11	0.02	0.76***
	(0.07)	(0.14)	(0.16)	(0.18)	(0.12)	(0.29)
Single parent with one or more children	0.10	0.27	-0.22	0.12	0.03	0.86*
	(0.08)	(0.23)	(0.21)	(0.18)	(0.13)	(0.49)
Patchwork family	0.36***	0.50**	0.42**	0.21	0.30*	-0.21
	(0.10)	(0.25)	(0.21)	(0.22)	(0.16)	(0.36)
Non-family shared household	-0.04	-0.04	-0.02	0.10	-0.07	-0.03
	(0.08)	(0.15)	(0.18)	(0.23)	(0.16)	(0.26)
Swiss	-0.19***	-0.07	-0.27***	-0.19	-0.20*	-0.30
	(0.05)	(0.09)	(0.09)	(0.14)	(0.11)	(0.26)
Agglomeration	0.16***					0.24**
	(0.04)					(0.10)
Countryside	0.33***		0.26***		0.19***	0.36***
	(0.04)		(0.06)		(0.06)	(0.12)
Female	-0.30***	-0.24***	-0.15**	-0.38***	-0.41***	-0.45***
	(0.03)	(0.07)	(0.06)	(0.08)	(0.06)	(0.10)
Owner	-0.09***	0.06	-0.21***	-0.03	-0.08	-0.10
	(0.03)	(0.12)	(0.07)	(0.08)	(0.06)	(0.10)
cut1	-1.37***	-1.60***	-1.42***	-0.47	-1.31***	-2.14***
	(0.18)	(0.43)	(0.40)	(0.48)	(0.43)	(0.81)
cut2	-0.38**	-0.65	-0.51	0.52	-0.24	-0.95
	(0.18)	(0.43)	(0.40)	(0.49)	(0.42)	(0.81)
cut3	0.30*	-0.04	0.17	1.21**	0.49	-0.15
	(0.18)	(0.43)	(0.40)	(0.49)	(0.42)	(0.81)
cut4	0.81***	0.46	0.67*	1.64***	1.07**	0.42
	(0.18)	(0.43)	(0.40)	(0.49)	(0.42)	(0.81)

cut5	1.15***	0.77*	1.05***	2.02***	1.43***	0.71
	(0.18)	(0.43)	(0.40)	(0.49)	(0.43)	(0.81)
cut6	1.46***	1.02**	1.38***	2.31***	1.80***	1.03
	(0.18)	(0.43)	(0.39)	(0.50)	(0.43)	(0.82)
cut7	1.67***	1.24***	1.56***	2.50***	2.08***	1.32
	(0.18)	(0.43)	(0.40)	(0.50)	(0.43)	(0.84)
cut8	1.88***	1.51***	1.75***	2.60***	2.35***	1.68**
	(0.18)	(0.44)	(0.40)	(0.51)	(0.43)	(0.85)
cut9	2.01***	1.71***	1.88***	2.66***	2.48***	1.96**
	(0.18)	(0.44)	(0.40)	(0.50)	(0.43)	(0.89)
cut10	2.35***	1.98***	2.33***	2.99***	2.77***	
	(0.19)	(0.44)	(0.41)	(0.52)	(0.45)	
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5385	987	1287	856	1530	687
Log-likelihood	-9447.5	-1810.4	-2434.6	-1405.3	-2633.2	-950.9

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordered Probit estimation

Table 41: Driven distance by car in km (ln) - odometer

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.00	0.01	0.01	-0.03*	0.01	0.00
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Injunctive norms	-0.03**	0.00	-0.03	0.01	-0.02	-0.06
	(0.01)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Descriptive norms	0.04**	0.06	0.03	0.02	0.03	0.02
	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Age (household)	-0.01***	-0.01	0.00	0.01	-0.00	-0.01
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Household size	-0.04	-0.01	0.01	0.04	-0.10	-0.15**
	(0.03)	(0.05)	(0.03)	(0.05)	(0.07)	(0.06)
Education in years	0.01	-0.01	-0.01	0.00	0.04***	0.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Income 3'000-4'459	0.17*	0.27	-0.03	0.07	0.23*	0.26
	(0.09)	(0.25)	(0.19)	(0.25)	(0.14)	(0.17)
Income 4'500-5'999	0.12	0.15	-0.09	0.25	-0.03	0.30*
	(0.08)	(0.23)	(0.16)	(0.20)	(0.15)	(0.16)
Income 6'000-8'999	0.21***	0.16	-0.04	0.53***	0.20	0.20
	(0.08)	(0.25)	(0.16)	(0.20)	(0.12)	(0.16)
Income 9'000-12'000	0.26***	0.25	0.09	0.36*	0.29**	0.29
	(0.08)	(0.24)	(0.16)	(0.22)	(0.13)	(0.18)
Income 12'000 or more	0.27***	0.25	-0.01	0.53**	0.25*	0.50***
	(0.09)	(0.25)	(0.17)	(0.22)	(0.14)	(0.19)
Couple without children	0.03	0.01	-0.03	0.06	0.09	0.11
	(0.05)	(0.11)	(0.09)	(0.11)	(0.11)	(0.10)
Couple with children	0.13	0.04	0.04	-0.04	0.33*	0.49***
	(0.09)	(0.15)	(0.13)	(0.18)	(0.19)	(0.18)
Single parent with one or more children	0.11	-0.01	0.32*	0.04	0.19	0.17
	(0.08)	(0.26)	(0.19)	(0.15)	(0.13)	(0.19)
Patchwork family	0.25***	0.22	0.19	0.06	0.36**	0.13
	(0.08)	(0.27)	(0.14)	(0.18)	(0.16)	(0.24)
Non-family shared household	0.01	-0.10	-0.04	-0.09	0.06	0.14
	(0.08)	(0.14)	(0.13)	(0.18)	(0.18)	(0.20)

Swiss	-0.13***	-0.15*	-0.22**	-0.14	-0.03	-0.13
	(0.04)	(0.09)	(0.09)	(0.11)	(0.07)	(0.13)
Agglomeration	0.11***					0.19***
	(0.03)					(0.07)
Countryside	0.18***		0.09		0.13***	0.20**
	(0.03)		(0.05)		(0.04)	(0.10)
Female	-0.09***	-0.15**	-0.00	-0.19***	-0.09**	-0.08
	(0.03)	(0.07)	(0.05)	(0.07)	(0.04)	(0.07)
Owner	-0.11***	-0.11	-0.23***	-0.11	-0.11**	-0.05
	(0.03)	(0.12)	(0.07)	(0.07)	(0.05)	(0.07)
Constant	9.46***	9.83***	10.01***	8.70***	8.88***	9.55***
	(0.17)	(0.38)	(0.29)	(0.39)	(0.39)	(0.58)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5185	926	1236	817	1494	679
R-squared	0.06	0.07	0.06	0.09	0.09	0.10

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. OLS estimation

Table 42: Flight costs (ln)

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	-0.04***	-0.03*	-0.03	-0.03	-0.10***	-0.05
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.04)
Injunctive norms	-0.02	0.05*	-0.05	-0.05	-0.03	-0.06
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.07)
Descriptive norms	0.01	-0.04	0.02	0.13***	-0.04	0.05
	(0.02)	(0.03)	(0.04)	(0.05)	(0.05)	(0.07)
Age	0.00***	0.02**	0.02**	-0.01	0.01	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	-0.02*	-0.05	0.05	-0.02	-0.00	-0.03
	(0.01)	(0.04)	(0.03)	(0.05)	(0.04)	(0.28)
Education in years	0.02*	-0.00	-0.00	0.03	0.03	0.03
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Income 3'000-4'459	0.18**	0.24*	0.19	0.14	0.04	0.23
	(0.09)	(0.14)	(0.22)	(0.25)	(0.29)	(0.25)
Income 4'500-5'999	0.31***	0.36***	0.13	0.45**	0.08	0.38
	(0.08)	(0.12)	(0.19)	(0.20)	(0.28)	(0.25)
Income 6'000-8'999	0.42***	0.49***	0.25	0.37**	0.32	0.56**
	(0.07)	(0.12)	(0.18)	(0.18)	(0.27)	(0.26)
Income 9'000-12'000	0.68***	0.64***	0.62***	0.80***	0.51*	0.70**
	(0.08)	(0.13)	(0.19)	(0.19)	(0.28)	(0.30)
Income 12'000 or more	1.00***	0.95***	0.85***	1.15***	0.88***	0.83**
	(0.08)	(0.13)	(0.19)	(0.20)	(0.28)	(0.35)
Couple without children	-0.05	-0.06	-0.12	-0.16	-0.02	0.03
	(0.05)	(0.09)	(0.11)	(0.12)	(0.13)	(0.33)
Couple with children	-0.13**	-0.12	-0.54***	-0.14	-0.02	-0.19
	(0.06)	(0.14)	(0.14)	(0.18)	(0.17)	(0.60)
Single parent with one or more children	0.02	-0.08	-0.05	0.13	0.07	0.16
	(0.08)	(0.16)	(0.20)	(0.18)	(0.18)	(0.57)
Patchwork family	-0.05	0.43*	-0.35	-0.20	-0.18	1.66***
	(0.10)	(0.23)	(0.25)	(0.24)	(0.20)	(0.56)
Non-family shared household	-0.20***	-0.12	-0.21	-0.27	-0.45	-0.40
	(0.07)	(0.11)	(0.18)	(0.28)	(0.30)	(0.40)

Swiss	-0.06	-0.05	0.01	-0.23**	-0.00	0.29
	(0.05)	(0.08)	(0.10)	(0.12)	(0.13)	(0.24)
Agglomeration	-0.07*					0.02
	(0.04)					(0.14)
Countryside	-0.18***		-0.12		-0.03	-0.42**
	(0.05)		(0.08)		(0.08)	(0.17)
Female	-0.16***	-0.05	-0.06	-0.24***	-0.36***	-0.09
	(0.03)	(0.06)	(0.07)	(0.08)	(0.08)	(0.13)
Owner	0.01	0.00	0.06	0.01	-0.02	-0.01
	(0.04)	(0.13)	(0.09)	(0.09)	(0.08)	(0.14)
Constant	6.72***	6.44***	6.30***	6.91***	6.76***	6.31***
	(0.17)	(0.34)	(0.43)	(0.50)	(0.54)	(1.10)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4710	1455	978	842	946	446
R-squared	0.10	0.11	0.12	0.17	0.16	0.13

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. OLS estimation

Table 43: Number of flights

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	-0.03***	-0.03***	-0.01	-0.05***	-0.06***	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
Injunctive norms	0.01	0.01	0.01	-0.03	0.01	0.03
	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.06)
Descriptive norms	0.03*	0.04	-0.02	0.11***	0.01	0.03
	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.06)
Age	-0.02***	-0.03***	-0.03***	-0.01	-0.00	-0.04***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	-0.01	-0.07**	0.01	0.00	-0.05	-0.30*
	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.15)
Education in years	0.02***	0.03**	0.04**	0.02	0.03*	0.03
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Income 3'000-4'459	0.14*	0.17	0.16	0.05	0.27	-0.00
	(0.08)	(0.11)	(0.19)	(0.21)	(0.28)	(0.25)
Income 4'500-5'999	0.32***	0.37***	0.29*	0.46**	0.45*	0.09
	(0.07)	(0.10)	(0.16)	(0.20)	(0.27)	(0.24)
Income 6'000-8'999	0.47***	0.50***	0.33**	0.57***	0.74***	0.49**
	(0.07)	(0.10)	(0.15)	(0.19)	(0.25)	(0.24)
Income 9'000-12'000	0.72***	0.74***	0.73***	0.90***	0.97***	0.49*
	(0.07)	(0.10)	(0.16)	(0.19)	(0.25)	(0.27)
Income 12'000 or more	1.05***	0.99***	1.07***	1.25***	1.39***	0.90***
	(0.08)	(0.10)	(0.16)	(0.20)	(0.26)	(0.29)
Couple without children	-0.17***	-0.17**	-0.26***	-0.15	-0.16	0.04
	(0.04)	(0.07)	(0.09)	(0.10)	(0.11)	(0.20)
Couple with children	-0.49***	-0.40***	-0.77***	-0.45***	-0.27*	0.42
	(0.07)	(0.12)	(0.13)	(0.15)	(0.14)	(0.38)
Single parent with one or more children	-0.05	-0.15	-0.11	-0.09	0.20	0.67
	(0.08)	(0.13)	(0.16)	(0.17)	(0.18)	(0.44)
Patchwork family	-0.24***	-0.18	-0.26	-0.46**	0.01	0.27
	(0.09)	(0.20)	(0.24)	(0.18)	(0.18)	(0.49)
Non-family shared household	-0.12*	-0.06	-0.28**	-0.26	-0.09	-0.09
	(0.06)	(0.09)	(0.14)	(0.17)	(0.21)	(0.30)

Swiss	-0.37***	-0.29***	-0.44***	-0.39***	-0.53***	-0.47**
	(0.04)	(0.05)	(0.08)	(0.09)	(0.09)	(0.22)
Agglomeration	-0.09***					0.04
	(0.03)					(0.11)
Countryside	-0.31***		-0.11*		-0.19***	-0.72***
	(0.04)		(0.06)		(0.07)	(0.14)
Female	-0.10***	-0.10**	-0.01	-0.13*	-0.11	-0.14
	(0.03)	(0.04)	(0.06)	(0.07)	(0.07)	(0.11)
Owner	0.02	0.02	0.05	-0.04	-0.05	0.02
	(0.03)	(0.08)	(0.08)	(0.07)	(0.07)	(0.10)
Constant	1.08***	1.63***	1.33***	0.72*	0.30	2.73***
	(0.15)	(0.25)	(0.32)	(0.41)	(0.53)	(0.96)
lnalpha	-0.58***	-1.04***	-0.69***	-0.50***	-0.39***	-0.19
	(0.04)	(0.07)	(0.09)	(0.09)	(0.09)	(0.13)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7451	1893	1525	1356	1700	921
Log-likelihood	-12716.5	-3682.2	-2621.9	-2286.5	-2560.7	-1286.8

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Negative binomial estimation

Table 44: Non-conventional heating system

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.02*	0.01	0.04*	0.01	0.02	0.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Injunctive norms	-0.02	-0.02	0.05	-0.10**	-0.02	-0.05
	(0.02)	(0.05)	(0.04)	(0.05)	(0.04)	(0.06)
Descriptive norms	0.01	0.02	-0.01	0.02	0.02	0.07
	(0.02)	(0.05)	(0.04)	(0.05)	(0.04)	(0.07)
Age (household)	-0.00	0.01	-0.00	-0.00	-0.01	-0.02***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	-0.00	-0.00	-0.09*	0.03	0.02	-0.03
	(0.02)	(0.04)	(0.05)	(0.06)	(0.05)	(0.09)
Education in years	0.01	0.02	-0.00	-0.06**	0.04**	0.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Income 3'000-4'459	-0.01	0.12	-0.20	-0.13	0.04	0.06
	(0.09)	(0.20)	(0.23)	(0.21)	(0.21)	(0.21)
Income 4'500-5'999	-0.09	-0.22	-0.27	-0.24	0.06	0.09
	(0.09)	(0.19)	(0.21)	(0.21)	(0.20)	(0.21)
Income 6'000-8'999	-0.02	-0.09	0.01	-0.12	0.03	-0.07
	(0.08)	(0.18)	(0.19)	(0.19)	(0.19)	(0.22)
Income 9'000-12'000	-0.05	0.02	-0.07	-0.25	-0.13	0.27
	(0.09)	(0.19)	(0.20)	(0.21)	(0.20)	(0.24)
Income 12'000 or more	-0.02	-0.10	-0.01	-0.08	-0.00	-0.07
	(0.09)	(0.20)	(0.21)	(0.22)	(0.21)	(0.31)
Couple without children	-0.04	-0.07	0.11	-0.15	-0.02	-0.02
	(0.05)	(0.12)	(0.14)	(0.14)	(0.12)	(0.16)
Couple with children	0.04	0.08	0.31	-0.15	-0.04	-0.10
	(0.07)	(0.17)	(0.19)	(0.21)	(0.18)	(0.35)
Single parent with one or more children	-0.25**	-0.29	-0.22	-0.10	-0.39**	-0.30
	(0.10)	(0.23)	(0.27)	(0.20)	(0.20)	(0.47)
Patchwork family	-0.07	-0.41	0.29	-0.23	-0.08	0.56
	(0.11)	(0.34)	(0.28)	(0.25)	(0.23)	(0.64)

Non-family shared household	-0.10	-0.01	-0.13	-0.33	-0.22	0.24
	(0.09)	(0.17)	(0.22)	(0.25)	(0.24)	(0.28)
Swiss	0.06	-0.17	0.22	0.06	0.15	0.08
	(0.06)	(0.12)	(0.14)	(0.15)	(0.14)	(0.28)
Agglomeration	0.12**					0.13
	(0.05)					(0.12)
Countryside	0.47***		0.30***		0.32***	0.53***
	(0.05)		(0.09)		(0.08)	(0.14)
Female	0.01	-0.05	-0.12	-0.00	0.05	-0.01
	(0.04)	(0.08)	(0.08)	(0.09)	(0.07)	(0.11)
Owner	0.21***	0.31**	0.19*	0.19*	0.24***	0.07
	(0.05)	(0.15)	(0.11)	(0.11)	(0.09)	(0.13)
Accommodation 2000-2009	-0.54***	-0.45**	-0.92***	-0.28	-0.56***	-0.72***
	(0.07)	(0.18)	(0.14)	(0.18)	(0.13)	(0.24)
Accommodation 1990-1999	-0.75***	-0.55***	-0.75***	-0.48**	-1.02***	-1.11***
	(0.07)	(0.18)	(0.15)	(0.20)	(0.14)	(0.26)
Accommodation 1980-1989	-0.93***	-0.95***	-1.09***	-0.70***	-1.00***	-1.35***
	(0.08)	(0.19)	(0.16)	(0.21)	(0.16)	(0.25)
Accommodation 1970-1979	-1.00***	-0.72***	-1.17***	-0.78***	-1.34***	-1.37***
	(0.08)	(0.18)	(0.18)	(0.21)	(0.19)	(0.25)
Accommodation 1960-1969	-0.84***	-0.51***	-1.12***	-0.81***	-1.06***	-1.35***
	(0.09)	(0.19)	(0.19)	(0.21)	(0.20)	(0.27)
Accommodation before 1960	-0.83***	-0.83***	-0.72***	-0.79***	-0.82***	-1.44***
	(0.07)	(0.17)	(0.15)	(0.19)	(0.16)	(0.26)
Accommodation do not know	-0.82***	-0.69***	-0.70**	-1.03***	-0.96**	-1.28
	(0.14)	(0.22)	(0.27)	(0.37)	(0.49)	(0.78)
Minergie yes	0.74***	0.83***	0.79***	0.71***	0.78***	0.60***
	(0.05)	(0.13)	(0.13)	(0.14)	(0.11)	(0.14)
Minergie do not know	0.16***	0.21*	0.24**	-0.05	0.26**	0.25*
	(0.05)	(0.11)	(0.12)	(0.14)	(0.12)	(0.14)
Renovations yes	0.01	0.01	-0.11	0.03	0.03	0.13
	(0.05)	(0.13)	(0.12)	(0.13)	(0.10)	(0.15)
Renovations do not know	-0.13**	-0.06	-0.33**	-0.00	-0.17	-0.01
	(0.06)	(0.13)	(0.13)	(0.15)	(0.15)	(0.18)
House	0.15***	-0.05	0.22**	0.10	0.32***	0.10
	(0.04)	(0.11)	(0.09)	(0.10)	(0.09)	(0.12)
Constant	-0.18	-0.57	-0.09	1.17**	-0.53	1.36
	(0.22)	(0.53)	(0.52)	(0.55)	(0.50)	(0.88)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6499	1389	1288	1244	1631	885
Log-likelihood	-3355.9	-623.6	-661.8	-596.0	-863.5	-446.7

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit estimation

Table 45: Non-conventional warm water system

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.03***	0.03	0.02	0.03	0.06***	0.04
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Injunctive norms	-0.00	-0.00	0.01	-0.04	-0.01	0.04
	(0.02)	(0.05)	(0.05)	(0.05)	(0.04)	(0.06)
Descriptive norms	0.03	0.09**	0.01	0.00	0.02	0.03
	(0.02)	(0.05)	(0.05)	(0.05)	(0.04)	(0.07)
Age (household)	-0.00***	-0.01	-0.01	-0.00	-0.00	-0.01

	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	-0.01	-0.03	-0.12*	0.05	-0.02	0.03
	(0.02)	(0.04)	(0.06)	(0.06)	(0.05)	(0.11)
Education in years	0.00	-0.01	-0.01	-0.05**	0.06***	0.00
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Income 3'000-4'459	-0.07	-0.08	-0.41*	-0.19	0.12	0.07
	(0.09)	(0.20)	(0.23)	(0.20)	(0.22)	(0.20)
Income 4'500-5'999	-0.12	-0.23	-0.55***	-0.34*	0.11	0.26
	(0.09)	(0.19)	(0.21)	(0.20)	(0.21)	(0.20)
Income 6'000-8'999	-0.12	-0.20	-0.32	-0.25	-0.02	0.07
	(0.08)	(0.18)	(0.20)	(0.19)	(0.21)	(0.20)
Income 9'000-12'000	-0.13	0.02	-0.31	-0.49**	-0.22	0.36
	(0.09)	(0.19)	(0.21)	(0.21)	(0.22)	(0.24)
Income 12'000 or more	-0.06	-0.02	-0.31	-0.16	-0.07	0.07
	(0.09)	(0.20)	(0.22)	(0.21)	(0.22)	(0.32)
Couple without children	0.00	-0.12	-0.05	-0.20	0.30**	-0.10
	(0.06)	(0.13)	(0.15)	(0.14)	(0.13)	(0.17)
Couple with children	0.07	0.14	0.23	-0.10	0.27	-0.16
	(0.08)	(0.17)	(0.21)	(0.20)	(0.17)	(0.35)
Single parent with one or more children	-0.12	-0.02	-0.20	0.02	-0.01	-0.98**
	(0.10)	(0.24)	(0.30)	(0.20)	(0.19)	(0.49)
Patchwork family	-0.15	-0.40	0.08	-0.22	0.11	-0.31
	(0.12)	(0.38)	(0.31)	(0.25)	(0.23)	(0.70)
Non-family shared household	-0.17*	-0.16	-0.15	-0.57**	0.13	-0.03
	(0.10)	(0.18)	(0.24)	(0.26)	(0.25)	(0.30)
Swiss	0.10	-0.15	0.27**	0.09	0.13	0.01
	(0.06)	(0.13)	(0.14)	(0.16)	(0.15)	(0.28)
Agglomeration	0.01					0.03
	(0.05)					(0.12)
Countryside	0.17***		0.17*		0.08	0.20
	(0.05)		(0.09)		(0.08)	(0.15)
Female	0.07*	0.01	-0.03	0.05	0.12	0.12
	(0.04)	(0.09)	(0.09)	(0.09)	(0.08)	(0.11)
Owner	0.18***	0.37**	0.26**	0.18*	0.28***	-0.09
	(0.05)	(0.15)	(0.11)	(0.11)	(0.09)	(0.13)
Accommodation 2000-2009	-0.65***	-0.58***	-0.86***	-0.58***	-0.74***	-0.58**
	(0.07)	(0.19)	(0.15)	(0.18)	(0.13)	(0.25)
Accommodation 1990-1999	-0.82***	-0.81***	-0.97***	-0.71***	-1.08***	-0.78***
	(0.07)	(0.19)	(0.15)	(0.21)	(0.14)	(0.26)
Accommodation 1980-1989	-0.89***	-0.88***	-1.23***	-0.70***	-0.93***	-0.99***
	(0.08)	(0.18)	(0.17)	(0.20)	(0.16)	(0.25)
Accommodation 1970-1979	-0.91***	-0.79***	-1.47***	-0.73***	-1.06***	-0.76***
	(0.08)	(0.18)	(0.18)	(0.21)	(0.18)	(0.25)
Accommodation 1960-1969	-0.84***	-0.61***	-1.26***	-0.88***	-0.86***	-0.96***
	(0.09)	(0.18)	(0.19)	(0.21)	(0.20)	(0.28)
Accommodation before 1960	-0.92***	-0.94***	-1.11***	-0.86***	-0.95***	-1.01***
	(0.07)	(0.17)	(0.16)	(0.18)	(0.16)	(0.27)
Accommodation do not know	-0.81***	-0.81***	-0.95***	-0.56	-0.92*	-1.06
	(0.15)	(0.24)	(0.31)	(0.35)	(0.48)	(0.75)
Minergie yes	0.84***	1.02***	0.75***	0.86***	0.86***	0.66***
	(0.06)	(0.14)	(0.13)	(0.14)	(0.11)	(0.15)
Minergie do not know	0.17***	0.29**	0.24**	0.06	0.10	0.20
	(0.05)	(0.12)	(0.12)	(0.14)	(0.12)	(0.14)
Renovations yes	0.07	0.07	0.21*	0.16	-0.02	0.02

	(0.05)	(0.13)	(0.13)	(0.13)	(0.10)	(0.15)
Renovations do not know	-0.05	0.05	0.05	0.06	-0.23	-0.10
	(0.06)	(0.13)	(0.13)	(0.14)	(0.15)	(0.18)
House	0.13***	-0.02	0.08	0.08	0.20**	0.22*
	(0.04)	(0.11)	(0.10)	(0.10)	(0.09)	(0.12)
Constant	-0.15	0.02	0.71	0.88	-1.41***	-0.27
	(0.22)	(0.54)	(0.54)	(0.55)	(0.53)	(0.86)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6165	1249	1203	1189	1609	862
Log-likelihood	-3208.5	-585.7	-624.1	-594.0	-808.8	-448.4

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit estimation

Table 46: Heating costs (ln)

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.00	-0.03	-0.00	0.02	0.01	-0.03*
	(0.01)	(0.03)	(0.04)	(0.02)	(0.02)	(0.02)
Injunctive norms	-0.00	-0.03	0.00	-0.03	-0.01	0.01
	(0.02)	(0.05)	(0.06)	(0.04)	(0.03)	(0.03)
Descriptive norms	-0.01	0.00	-0.06	0.01	0.07**	-0.04
	(0.02)	(0.05)	(0.06)	(0.04)	(0.03)	(0.04)
Age (household)	0.01***	-0.00	0.01	-0.00	0.01**	0.00
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Household size	-0.01	-0.00	0.06	0.01	0.02	-0.05
	(0.02)	(0.07)	(0.07)	(0.04)	(0.04)	(0.05)
Education in years	0.01*	0.05*	0.01	-0.00	0.01	-0.00
	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Income 3'000-4'459	0.07	-0.20	-0.08	0.39**	-0.13	0.16
	(0.09)	(0.28)	(0.45)	(0.19)	(0.18)	(0.11)
Income 4'500-5'999	0.09	-0.15	0.11	0.30	-0.17	0.15
	(0.08)	(0.22)	(0.39)	(0.19)	(0.16)	(0.11)
Income 6'000-8'999	0.12	0.23	0.35	0.26	-0.32**	0.20*
	(0.08)	(0.21)	(0.38)	(0.18)	(0.16)	(0.11)
Income 9'000-12'000	0.17*	0.22	0.35	0.32*	-0.27*	0.24*
	(0.09)	(0.22)	(0.41)	(0.18)	(0.16)	(0.14)
Income 12'000 or more	0.18*	0.30	0.15	0.44**	-0.27	0.36**
	(0.09)	(0.24)	(0.40)	(0.19)	(0.17)	(0.17)
Couple without children	0.08	-0.00	-0.24	0.04	0.16	0.17**
	(0.05)	(0.15)	(0.22)	(0.10)	(0.11)	(0.09)
Couple with children	0.12	-0.01	-0.31	0.10	0.15	-0.05
	(0.08)	(0.25)	(0.29)	(0.15)	(0.14)	(0.17)
Single parent with one or more children	0.04	-0.20	-0.92**	-0.14	0.29**	0.24
	(0.10)	(0.46)	(0.37)	(0.18)	(0.14)	(0.19)
Patchwork family	0.22**	0.26	-0.19	0.16	0.25	-0.26
	(0.10)	(0.36)	(0.42)	(0.17)	(0.18)	(0.31)
Non-family shared household	-0.03	0.04	-0.74	0.02	0.36**	0.00
	(0.10)	(0.20)	(0.50)	(0.23)	(0.16)	(0.15)
Swiss	0.03	0.09	-0.18	0.09	0.10	0.02
	(0.06)	(0.13)	(0.18)	(0.13)	(0.11)	(0.22)
Agglomeration	0.05					0.09
	(0.04)					(0.07)

Countryside	0.10**		-0.20*		0.09	0.17**
	(0.05)		(0.12)		(0.07)	(0.08)
Female	0.06*	-0.00	0.22*	0.07	-0.06	0.17***
	(0.03)	(0.09)	(0.12)	(0.07)	(0.06)	(0.06)
Owner	0.10**	0.24	0.38**	0.09	0.02	-0.07
	(0.04)	(0.18)	(0.17)	(0.08)	(0.09)	(0.07)
Accommodation 2000-2009	-0.04	-0.41**	0.07	0.02	-0.08	-0.05
	(0.06)	(0.18)	(0.19)	(0.14)	(0.10)	(0.14)
Accommodation 1990-1999	0.07	-0.06	0.12	0.20	-0.06	-0.12
	(0.06)	(0.19)	(0.28)	(0.15)	(0.11)	(0.12)
Accommodation 1980-1989	0.17**	-0.13	0.27	0.24*	0.05	-0.03
	(0.07)	(0.24)	(0.20)	(0.14)	(0.12)	(0.13)
Accommodation 1970-1979	0.10	-0.29	0.46*	0.26*	-0.13	-0.02
	(0.07)	(0.21)	(0.26)	(0.14)	(0.15)	(0.12)
Accommodation 1960-1969	0.07	-0.23	0.03	0.13	0.11	-0.05
	(0.08)	(0.22)	(0.32)	(0.16)	(0.15)	(0.15)
Accommodation before 1960	0.20***	-0.07	0.60**	0.19	0.05	0.10
	(0.07)	(0.19)	(0.24)	(0.13)	(0.13)	(0.12)
Accommodation do not know	0.00	-0.13	-0.47	-0.06	-0.04	0.45
	(0.14)	(0.24)	(0.40)	(0.35)	(0.25)	(0.30)
Accommodation size (ln)	0.29***	0.66***	0.05	0.35***	0.31***	0.37***
	(0.06)	(0.22)	(0.18)	(0.12)	(0.10)	(0.11)
Minergie yes	-0.18***	-0.76***	0.05	-0.15	-0.16	-0.17*
	(0.05)	(0.17)	(0.17)	(0.11)	(0.10)	(0.09)
Minergie do not know	-0.00	0.11	-0.16	-0.03	-0.06	0.08
	(0.05)	(0.14)	(0.22)	(0.10)	(0.11)	(0.08)
Renovations yes	0.00	0.02	0.12	0.01	0.03	0.06
	(0.05)	(0.17)	(0.19)	(0.10)	(0.08)	(0.07)
Renovations do not know	0.01	0.19	0.12	0.01	-0.03	-0.06
	(0.05)	(0.15)	(0.20)	(0.11)	(0.12)	(0.09)
Flat in a building with less than 5 flats	-0.02	0.17	0.10	0.13	-0.11	-0.04
	(0.06)	(0.20)	(0.24)	(0.11)	(0.12)	(0.10)
Flat in a building with 5 to 10 flats	-0.13***	0.16	-0.04	-0.11	-0.20*	-0.21**
	(0.05)	(0.15)	(0.18)	(0.10)	(0.10)	(0.09)
Flat in a building with more than 10 flats	-0.12**	0.22	-0.07	-0.14	-0.30**	-0.17*
	(0.06)	(0.16)	(0.22)	(0.11)	(0.13)	(0.09)
Number of rooms	0.07***	-0.06	0.04	0.04	0.08*	0.08*
	(0.02)	(0.07)	(0.06)	(0.05)	(0.04)	(0.05)
Number of bathrooms	0.06*	-0.08	0.21*	0.04	0.06	0.09*
	(0.03)	(0.14)	(0.12)	(0.06)	(0.05)	(0.05)
Number of other/garages	0.02	0.04	0.06	0.02	0.02	0.00
	(0.02)	(0.05)	(0.06)	(0.03)	(0.02)	(0.03)
Heating: Gas	0.07	0.47**	0.29	-0.29*	0.17	-0.08
	(0.07)	(0.20)	(0.35)	(0.17)	(0.12)	(0.15)
Heating: Electricity	0.04	-0.30	-0.05	-0.14	0.48***	0.23

	(0.09)	(0.25)	(0.28)	(0.19)	(0.14)	(0.17)
Heating: Wood	-0.19*	0.61*	0.19	-0.89***	-0.31*	0.12
	(0.11)	(0.37)	(0.28)	(0.20)	(0.17)	(0.33)
Heating: Heat pump	-0.10	0.58*	0.30	-0.51**	-0.12	-0.20
	(0.08)	(0.31)	(0.29)	(0.23)	(0.13)	(0.14)
Heating: Solar	-0.06	0.49	-0.11	-0.11	0.18	0.05
	(0.25)	(0.60)	(0.76)	(0.23)	(0.41)	(0.43)
Heating: District	0.24**	0.71**	0.93	-0.15	0.16	0.23
	(0.12)	(0.29)	(0.59)	(0.18)	(0.31)	(0.19)
Heating: Other	0.02	1.03	0.10	-0.61**	0.17	-0.24
	(0.17)	(0.74)	(0.83)	(0.29)	(0.29)	(0.23)
Heating: do not know	0.01	0.25	0.24	-0.28	0.00	0.06
	(0.10)	(0.19)	(0.28)	(0.22)	(0.26)	(0.30)
Warm water: Gas	-0.05	-0.18	-0.07	0.32*	-0.26*	0.05
	(0.08)	(0.23)	(0.38)	(0.19)	(0.16)	(0.16)
Warm water: Electricity	-0.07	-0.18	-0.01	0.10	-0.15	-0.15
	(0.06)	(0.19)	(0.20)	(0.13)	(0.12)	(0.13)
Warm water: Wood	0.04	-0.12	-0.01	0.66*	-0.05	-0.09
	(0.15)	(0.46)	(0.41)	(0.34)	(0.29)	(0.35)
Warm water: Heat pump	-0.20*	-0.65**	-0.48	0.10	-0.13	-0.03
	(0.10)	(0.32)	(0.30)	(0.23)	(0.16)	(0.16)
Warm water: Solar	-0.26***	-0.40	-0.95**	0.14	-0.27**	-0.16
	(0.08)	(0.31)	(0.43)	(0.19)	(0.13)	(0.15)
Warm water: District	-0.10	-0.42	-0.57	0.27	-0.08	-0.28
	(0.13)	(0.36)	(0.59)	(0.19)	(0.33)	(0.22)
Warm water: Other	-0.26	-0.63	-0.59	0.12	-0.32	0.07
	(0.17)	(0.67)	(1.23)	(0.41)	(0.27)	(0.37)
Warm water: do not know	-0.04	-0.21	-0.16	0.16	-0.11	-0.14
	(0.08)	(0.18)	(0.26)	(0.17)	(0.17)	(0.21)
Heating bill: accomm. size	0.18***	0.25**	0.06	0.20**	0.32***	0.15**
	(0.04)	(0.10)	(0.17)	(0.09)	(0.09)	(0.07)
Heating bill: consumption & size	0.12**	0.13	0.37**	0.07	0.16	0.09
	(0.05)	(0.12)	(0.17)	(0.08)	(0.10)	(0.09)
Constant	4.24***	3.20***	5.08***	4.52***	4.31***	4.77***
	(0.30)	(0.91)	(1.02)	(0.57)	(0.63)	(0.64)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2863	518	313	678	725	625
R-squared	0.22	0.29	0.39	0.28	0.26	0.31

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. OLS estimation

Table 47: Temperature

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	-0.02***	-0.04**	-0.01	-0.02	-0.01	-0.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Injunctive norms	-0.08***	-0.06	-0.08**	-0.10***	-0.07**	-0.10**
	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Descriptive norms	-0.00	-0.02	-0.01	0.04	-0.01	0.00
	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)
Age (household)	0.01***	0.00	0.01	0.01*	0.01***	0.01**
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Household size	0.00	-0.03	0.01	-0.12***	0.06*	0.07

	(0.02)	(0.04)	(0.03)	(0.04)	(0.04)	(0.09)
Education in years	-0.03***	-0.00	-0.04**	-0.03*	-0.05***	-0.01
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Income 3'000-4'459	0.15**	-0.06	0.21	0.12	0.23	0.19
	(0.07)	(0.17)	(0.19)	(0.18)	(0.16)	(0.14)
Income 4'500-5'999	0.17**	0.02	0.19	0.12	0.20	0.41***
	(0.07)	(0.15)	(0.17)	(0.18)	(0.16)	(0.15)
Income 6'000-8'999	0.19***	0.04	0.30*	0.06	0.35**	0.30**
	(0.07)	(0.14)	(0.17)	(0.18)	(0.14)	(0.14)
Income 9'000-12'000	0.26***	0.15	0.39**	0.20	0.37**	0.30*
	(0.07)	(0.15)	(0.17)	(0.19)	(0.15)	(0.16)
Income 12'000 or more	0.27***	0.12	0.40**	0.21	0.39**	0.33
	(0.07)	(0.16)	(0.18)	(0.20)	(0.16)	(0.21)
Couple without children	0.08*	-0.01	0.16	0.27***	0.06	-0.08
	(0.04)	(0.10)	(0.11)	(0.10)	(0.10)	(0.13)
Couple with children	0.13**	0.20	0.14	0.38**	0.05	0.00
	(0.06)	(0.15)	(0.13)	(0.15)	(0.13)	(0.24)
Single parent with one or more children	0.09	0.47***	0.17	0.16	0.03	-0.12
	(0.07)	(0.17)	(0.18)	(0.15)	(0.15)	(0.31)
Patchwork family	0.15	0.25	0.28	0.58***	-0.11	-0.41
	(0.09)	(0.26)	(0.17)	(0.21)	(0.16)	(0.47)
Non-family shared household	-0.01	-0.09	0.04	-0.07	0.22	0.08
	(0.07)	(0.13)	(0.17)	(0.21)	(0.18)	(0.19)
Swiss	-0.03	-0.16*	-0.17*	0.25**	-0.02	0.22
	(0.05)	(0.09)	(0.09)	(0.13)	(0.10)	(0.21)
Agglomeration	-0.01					-0.07
	(0.03)					(0.09)
Countryside	0.01		0.10		-0.05	-0.02
	(0.04)		(0.07)		(0.06)	(0.10)
Female	0.02	0.12*	0.05	-0.02	-0.03	0.05
	(0.03)	(0.06)	(0.06)	(0.07)	(0.06)	(0.08)
Owner	0.06	0.20*	0.01	0.06	0.07	-0.03
	(0.04)	(0.11)	(0.08)	(0.08)	(0.07)	(0.09)
Accommodation 2000-2009	-0.03	0.19	-0.05	-0.12	-0.09	0.06
	(0.05)	(0.14)	(0.11)	(0.14)	(0.09)	(0.20)
Accommodation 1990-1999	0.03	0.19	0.06	-0.10	-0.01	0.04
	(0.05)	(0.15)	(0.11)	(0.16)	(0.10)	(0.18)
Accommodation 1980-1989	-0.08	-0.04	-0.11	-0.23	-0.03	-0.05
	(0.06)	(0.14)	(0.13)	(0.15)	(0.12)	(0.19)
Accommodation 1970-1979	-0.03	0.21	-0.11	-0.17	-0.07	-0.07
	(0.06)	(0.14)	(0.13)	(0.16)	(0.13)	(0.19)
Accommodation 1960-1969	-0.14**	0.01	-0.20	-0.20	-0.27*	0.01
	(0.07)	(0.14)	(0.14)	(0.17)	(0.15)	(0.20)
Accommodation before 1960	-0.23***	0.05	-0.33***	-0.36**	-0.32***	-0.21
	(0.06)	(0.13)	(0.12)	(0.15)	(0.12)	(0.19)
Accommodation do not know	-0.20*	0.02	-0.19	-0.40	-0.57**	0.36
	(0.11)	(0.17)	(0.25)	(0.32)	(0.26)	(0.50)
Renovations yes	-0.06	-0.23**	-0.07	0.00	0.03	-0.06
	(0.04)	(0.11)	(0.09)	(0.10)	(0.07)	(0.11)
Renovations do not know	-0.01	-0.16	-0.12	-0.06	0.13	0.21
	(0.05)	(0.11)	(0.10)	(0.12)	(0.11)	(0.14)
Minergie yes	0.00	0.14	-0.12	-0.04	0.03	-0.07
	(0.04)	(0.11)	(0.09)	(0.12)	(0.08)	(0.11)
Minergie do not know	-0.02	0.14	-0.12	-0.03	-0.19**	0.06

	(0.04)	(0.09)	(0.08)	(0.10)	(0.09)	(0.09)
Flat in a building with less than 5 flats	0.17***	0.25**	0.17*	0.05	0.20**	0.04
	(0.04)	(0.10)	(0.10)	(0.11)	(0.09)	(0.12)
Flat in a building with 5 to 10 flats	0.22***	0.25***	0.17**	0.17*	0.31***	0.13
	(0.04)	(0.09)	(0.08)	(0.09)	(0.08)	(0.10)
Flat in a building with more than 10 flats	0.24***	0.28***	0.17	0.21*	0.19*	0.21*
	(0.05)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
Gas	0.01	0.06	0.04	-0.03	-0.05	-0.05
	(0.04)	(0.09)	(0.11)	(0.09)	(0.08)	(0.08)
Electricity	0.03	-0.10	-0.01	0.17	0.06	-0.08
	(0.05)	(0.10)	(0.11)	(0.16)	(0.12)	(0.14)
Wood	-0.12**	0.00	-0.07	-0.15	-0.13	-0.14
	(0.06)	(0.20)	(0.12)	(0.14)	(0.10)	(0.15)
Heat pump	0.04	-0.17	-0.00	0.04	0.11	-0.02
	(0.04)	(0.11)	(0.09)	(0.12)	(0.08)	(0.14)
Solar	-0.15	-0.85***	0.15	-0.01	-0.36	-0.11
	(0.12)	(0.24)	(0.19)	(0.28)	(0.32)	(0.36)
District heating	0.02	0.03	0.19	-0.11	0.03	-0.08
	(0.06)	(0.12)	(0.15)	(0.13)	(0.13)	(0.13)
Constant	20.85***	21.14***	21.19***	21.03***	20.83***	20.38***
	(0.16)	(0.41)	(0.40)	(0.43)	(0.38)	(0.63)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5982	1229	1183	1155	1540	838
R-squared	0.09	0.10	0.11	0.12	0.11	0.14

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. OLS estimation

Table 48: Index for energy saving heating behavior

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.01***	0.01**	0.02***	-0.00	0.01*	0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Injunctive norms	0.02***	0.01	0.02*	0.03**	0.03***	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Descriptive norms	0.00	0.01	0.00	0.00	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Age	0.00***	0.00	-0.00	0.00	0.00***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Household size	-0.00	0.01	-0.01	-0.02	-0.01	0.03
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Education in years	0.00	-0.00	0.01	0.01*	-0.00	-0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Income 3'000-4'459	0.01	-0.01	-0.03	0.05	-0.02	0.05
	(0.03)	(0.05)	(0.07)	(0.06)	(0.05)	(0.05)
Income 4'500-5'999	0.00	0.01	0.01	-0.00	0.03	-0.05
	(0.02)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)
Income 6'000-8'999	-0.00	0.01	-0.05	0.03	-0.01	0.01
	(0.02)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)
Income 9'000-12'000	-0.00	0.01	-0.08	0.03	0.01	0.06
	(0.02)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)

Income 12'000 or more	-0.03	0.02	-0.14**	-0.04	0.01	-0.12
	(0.03)	(0.05)	(0.07)	(0.07)	(0.05)	(0.09)
Couple without children	0.04***	-0.01	0.03	0.15***	0.04	-0.03
	(0.01)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
Couple with children	0.07***	0.03	0.06	0.22***	0.05	-0.07
	(0.02)	(0.04)	(0.05)	(0.05)	(0.04)	(0.08)
Single parent with one or more children	-0.02	-0.12	0.01	0.07	0.00	-0.06
	(0.03)	(0.08)	(0.07)	(0.05)	(0.05)	(0.11)
Patchwork family	0.05*	-0.05	0.02	0.15**	0.06	0.05
	(0.03)	(0.08)	(0.07)	(0.06)	(0.05)	(0.12)
Non-family shared household	0.08***	0.04	0.07	0.25***	-0.05	-0.02
	(0.02)	(0.04)	(0.06)	(0.05)	(0.07)	(0.07)
Swiss	0.00	0.02	-0.03	0.05	0.07*	-0.09
	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.07)
Agglomeration	0.02					0.06**
	(0.01)					(0.03)
Countryside	0.01		-0.02		0.02	0.08**
	(0.01)		(0.02)		(0.02)	(0.04)
Female	0.04***	0.08***	0.02	0.05**	0.00	-0.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Owner	0.06***	0.06	0.07**	0.11***	-0.03	0.13***
	(0.01)	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)
Accommodation 2000-2009	-0.04**	-0.05	0.00	0.03	-0.08**	-0.11*
	(0.02)	(0.05)	(0.04)	(0.05)	(0.03)	(0.07)
Accommodation 1990-1999	-0.03	-0.05	-0.03	0.01	-0.07*	-0.06
	(0.02)	(0.06)	(0.05)	(0.06)	(0.04)	(0.06)
Accommodation 1980-1989	-0.02	0.02	-0.03	0.06	-0.10**	-0.11*
	(0.02)	(0.05)	(0.04)	(0.06)	(0.04)	(0.06)
Accommodation 1970-1979	0.03	0.02	0.01	0.03	-0.00	0.01
	(0.02)	(0.05)	(0.05)	(0.06)	(0.04)	(0.06)
Accommodation 1960-1969	0.03	0.05	0.02	0.10	-0.06	-0.05
	(0.02)	(0.05)	(0.05)	(0.06)	(0.05)	(0.07)
Accommodation before 1960	0.05**	0.07	0.02	0.12**	-0.01	0.02
	(0.02)	(0.05)	(0.04)	(0.06)	(0.04)	(0.06)
Accommodation do not know	-0.03	-0.02	-0.10	-0.10	-0.06	-0.04
	(0.03)	(0.06)	(0.07)	(0.11)	(0.12)	(0.14)
Accommodation size (ln)	0.01	-0.04	0.01	0.00	0.04	-0.06
	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Minergie yes	-0.02	-0.09**	-0.01	0.03	-0.02	0.00
	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Minergie do not know	-0.03**	-0.04	0.00	-0.05	-0.06*	-0.03
	(0.01)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)
Renovations yes	0.02	0.01	0.03	0.00	0.03	0.04
	(0.01)	(0.03)	(0.03)	(0.04)	(0.02)	(0.04)
Renovations do not know	0.01	-0.01	0.05	0.06	-0.02	-0.09*
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
Flat in a building with less than 5 flats	-0.07***	-0.13***	-0.07**	-0.02	-0.13***	0.00
	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
Flat in a building with 5 to 10 flats	-0.07***	-0.05*	-0.12***	-0.03	-0.11***	-0.12***
	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Flat in a building with more than 10 flats	-0.10***	-0.10***	-0.15***	-0.12***	-0.10***	-0.06

	(0.02)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
Number of rooms	0.01*	0.02*	0.02	-0.01	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Number of bathrooms	-0.01	-0.01	-0.00	-0.03	-0.02	0.03
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Number of other/garages	-0.00	-0.01	0.01*	-0.01	-0.01	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Heating: Gas	-0.02	-0.01	0.00	-0.06	-0.04	0.07
	(0.02)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
Heating: Electricity	-0.01	-0.01	0.05	-0.09	-0.01	0.03
	(0.02)	(0.05)	(0.05)	(0.06)	(0.04)	(0.06)
Heating: Wood	0.05**	0.04	0.13**	0.00	0.01	-0.01
	(0.02)	(0.08)	(0.05)	(0.05)	(0.03)	(0.06)
Heating: Heat pump	-0.09***	0.03	-0.06	-0.11	-0.10***	-0.20***
	(0.02)	(0.06)	(0.05)	(0.07)	(0.04)	(0.06)
Heating: Solar	0.00	0.06	-0.03	-0.01	-0.00	0.08
	(0.05)	(0.16)	(0.09)	(0.12)	(0.11)	(0.10)
Heating: District	-0.07*	-0.18**	-0.08	-0.10	0.08	-0.01
	(0.04)	(0.08)	(0.09)	(0.08)	(0.07)	(0.10)
Heating: Other	0.05	0.09	0.10	-0.08	0.05	0.13
	(0.05)	(0.14)	(0.18)	(0.11)	(0.06)	(0.10)
Heating: do not know	-0.03	-0.01	-0.04	-0.05	-0.01	-0.02
	(0.02)	(0.04)	(0.05)	(0.06)	(0.09)	(0.09)
Warm water: Gas	0.04	0.07	-0.01	0.04	0.08	-0.03
	(0.03)	(0.05)	(0.08)	(0.05)	(0.06)	(0.06)
Warm water: Electricity	0.03*	0.07*	-0.01	-0.01	0.05*	0.01
	(0.02)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
Warm water: Wood	-0.05	0.08	-0.21**	0.03	-0.02	-0.00
	(0.04)	(0.13)	(0.09)	(0.08)	(0.05)	(0.11)
Warm water: Heat pump	0.04	0.05	0.04	0.03	-0.02	0.13*
	(0.03)	(0.06)	(0.05)	(0.07)	(0.04)	(0.07)
Warm water: Solar	0.04*	0.05	0.02	0.03	0.04	-0.02
	(0.02)	(0.07)	(0.06)	(0.06)	(0.04)	(0.05)
Warm water: District	0.08*	0.24***	0.10	0.06	-0.05	0.03
	(0.04)	(0.08)	(0.10)	(0.08)	(0.07)	(0.11)
Warm water: Other	0.03	0.08	-0.09	0.15	-0.05	0.09
	(0.05)	(0.09)	(0.15)	(0.12)	(0.08)	(0.10)
Warm water: do not know	0.01	0.03	0.01	0.01	-0.05	0.09
	(0.02)	(0.04)	(0.05)	(0.05)	(0.07)	(0.08)
Constant	0.41***	0.53***	0.49**	0.33	0.30*	1.28***
	(0.08)	(0.19)	(0.20)	(0.22)	(0.17)	(0.32)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7379	1878	1513	1343	1683	906
Log-likelihood	-10984.7	-2761.5	-2212.5	-2014.5	-2494.2	-1359.4

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Poisson

Table 49: Energy-saving venting behavior

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.06***	0.07***	0.08***	0.05***	0.04***	0.04*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Injunctive norms	0.02	0.04	0.04	0.02	0.02	-0.01
	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)

Descriptive norms	-0.02	-0.02	-0.07*	0.07	-0.06	-0.02
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)
Age	0.00***	0.01	0.02***	0.00	0.01	-0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	-0.03**	-0.05*	-0.06	0.03	0.02	-0.04
	(0.01)	(0.03)	(0.05)	(0.05)	(0.04)	(0.07)
Education in years	0.01	0.01	0.01	0.03	-0.02	-0.03
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Income 3'000-4'459	0.16**	0.35***	0.01	0.08	0.22	-0.08
	(0.07)	(0.12)	(0.17)	(0.16)	(0.17)	(0.16)
Income 4'500-5'999	0.12*	0.28**	-0.05	0.07	0.14	-0.13
	(0.06)	(0.12)	(0.15)	(0.15)	(0.16)	(0.16)
Income 6'000-8'999	0.15**	0.29***	-0.02	0.07	0.22	-0.14
	(0.06)	(0.11)	(0.14)	(0.14)	(0.15)	(0.16)
Income 9'000-12'000	0.20***	0.34***	0.07	0.06	0.29*	-0.03
	(0.07)	(0.12)	(0.16)	(0.16)	(0.16)	(0.18)
Income 12'000 or more	0.12*	0.46***	-0.24	-0.08	0.19	-0.19
	(0.07)	(0.13)	(0.16)	(0.17)	(0.17)	(0.26)
Couple without children	0.16***	0.13	0.23**	0.11	0.12	0.25*
	(0.04)	(0.08)	(0.11)	(0.11)	(0.10)	(0.14)
Couple with children	0.23***	0.21*	0.19	0.23	0.09	0.32
	(0.06)	(0.12)	(0.17)	(0.18)	(0.15)	(0.28)
Single parent with one or more children	-0.06	-0.20	-0.31*	0.28*	0.02	-0.24
	(0.07)	(0.15)	(0.18)	(0.16)	(0.15)	(0.30)
Patchwork family	0.21**	0.21	-0.28	0.45**	0.28	-1.03**
	(0.10)	(0.23)	(0.24)	(0.23)	(0.19)	(0.48)
Non-family shared household	0.03	0.05	0.03	-0.18	0.20	0.00
	(0.07)	(0.11)	(0.17)	(0.20)	(0.22)	(0.24)
Swiss	0.27***	0.25***	0.12	0.34***	0.46***	0.44**
	(0.05)	(0.08)	(0.10)	(0.12)	(0.12)	(0.21)
Agglomeration	-0.00					0.08
	(0.04)					(0.11)
Countryside	0.03		-0.00		0.09	-0.20*
	(0.04)		(0.07)		(0.07)	(0.12)
Female	0.08***	0.05	0.05	0.07	0.03	0.23**
	(0.03)	(0.06)	(0.07)	(0.07)	(0.07)	(0.10)
Owner	-0.02	-0.10	0.04	0.05	0.05	-0.11
	(0.04)	(0.11)	(0.08)	(0.08)	(0.07)	(0.10)
cut1	-1.09***	-0.74**	-0.98***	-0.45	-1.45***	-3.01***
	(0.16)	(0.35)	(0.37)	(0.46)	(0.46)	(0.82)
cut2	-0.52***	-0.10	-0.34	-0.01	-0.89*	-2.45***
	(0.16)	(0.35)	(0.37)	(0.46)	(0.46)	(0.81)
cut3	0.69***	1.07***	0.67*	1.27***	0.47	-0.70
	(0.16)	(0.34)	(0.37)	(0.46)	(0.46)	(0.81)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7301	1878	1491	1319	1653	904
Log-likelihood	-6582.5	-1734.0	-1385.5	-1149.5	-1406.6	-674.3

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordered Probit

Table 50: Number of showers/baths (household)

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.00	0.01*	0.01**	-0.00	-0.00	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Injunctive norms	0.00	0.01	0.01	0.01	-0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Descriptive norms	-0.00	0.01	-0.02	-0.01	0.02	-0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)
Age (household)	-0.01***	-0.00*	-0.00	-0.01***	-0.01***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Household size	0.07***	0.09***	0.08**	0.08***	0.10***	-0.04
	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)
Education in years	0.00	0.00	0.01	0.01	-0.00	0.02*
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income 3'000-4'459	0.01	-0.05	0.00	0.01	0.13	0.04
	(0.03)	(0.05)	(0.07)	(0.08)	(0.08)	(0.07)
Income 4'500-5'999	0.07**	-0.00	0.07	0.11	0.10	0.13*
	(0.03)	(0.05)	(0.07)	(0.07)	(0.08)	(0.07)
Income 6'000-8'999	0.13***	0.01	0.09	0.15**	0.30***	0.15*
	(0.03)	(0.05)	(0.07)	(0.07)	(0.07)	(0.08)
Income 9'000-12'000	0.19***	0.11**	0.18**	0.14*	0.30***	0.24***
	(0.03)	(0.05)	(0.07)	(0.07)	(0.07)	(0.09)
Income 12'000 or more	0.27***	0.18***	0.24***	0.21***	0.42***	0.25*
	(0.03)	(0.05)	(0.07)	(0.08)	(0.08)	(0.13)
Couple without children	0.30***	0.33***	0.30***	0.37***	0.27***	0.31***
	(0.02)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)
Couple with children	0.47***	0.41***	0.37***	0.51***	0.44***	0.49***
	(0.05)	(0.09)	(0.10)	(0.08)	(0.07)	(0.13)
Single parent with one or more children	0.35***	0.38***	0.37***	0.37***	0.27***	0.14
	(0.04)	(0.07)	(0.09)	(0.07)	(0.07)	(0.19)
Patchwork family	0.48***	0.35***	0.48***	0.50***	0.40***	-0.26
	(0.06)	(0.12)	(0.13)	(0.09)	(0.09)	(0.19)
Non-family shared household	0.34***	0.36***	0.46***	0.19**	0.06	0.31***
	(0.04)	(0.07)	(0.08)	(0.09)	(0.09)	(0.12)
Swiss	0.03	0.00	-0.00	0.04	0.07	-0.01
	(0.02)	(0.03)	(0.04)	(0.05)	(0.06)	(0.08)
Agglomeration	-0.00					-0.05
	(0.02)					(0.05)
Countryside	-0.01		-0.01		-0.01	-0.05
	(0.02)		(0.03)		(0.03)	(0.06)
Female	0.01	-0.02	0.00	-0.01	0.04	0.06
	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.05)
Owner	-0.01	-0.19***	-0.02	-0.07*	0.01	0.04
	(0.02)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)
Constant	1.82***	1.73***	1.45***	1.81***	1.86***	3.20***
	(0.07)	(0.14)	(0.17)	(0.19)	(0.18)	(0.34)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7445	1891	1525	1353	1700	920
R-squared	0.31	0.27	0.28	0.36	0.37	0.22

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. OLS estimation

Table 51: Automatically turn off shower (strongly disagree to strongly agree)

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.01**	-0.00	-0.01	0.00	0.05***	0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Injunctive norms	0.06***	0.04	0.06*	0.07*	0.05	0.18***
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
Descriptive norms	0.01	0.01	0.02	0.04	0.02	-0.08
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)
Age	0.01***	0.01*	0.00	0.00	0.01*	-0.02**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	0.00	-0.00	-0.01	0.03	-0.00	0.08
	(0.01)	(0.03)	(0.04)	(0.05)	(0.04)	(0.08)
Education in years	0.00	0.02	0.03	0.02	-0.03*	-0.03
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Income 3'000-4'459	0.01	0.26**	-0.16	0.09	-0.15	-0.18
	(0.07)	(0.13)	(0.16)	(0.16)	(0.17)	(0.17)
Income 4'500-5'999	-0.00	0.01	-0.17	0.10	0.01	-0.04
	(0.06)	(0.11)	(0.14)	(0.16)	(0.16)	(0.17)
Income 6'000-8'999	-0.08	-0.01	-0.16	-0.11	-0.07	-0.28*
	(0.06)	(0.11)	(0.14)	(0.15)	(0.15)	(0.17)
Income 9'000-12'000	-0.08	-0.09	-0.12	-0.04	-0.12	0.05
	(0.06)	(0.11)	(0.15)	(0.16)	(0.16)	(0.20)
Income 12'000 or more	-0.15**	-0.05	-0.32**	-0.13	-0.19	-0.44
	(0.07)	(0.12)	(0.16)	(0.17)	(0.17)	(0.30)
Couple without children	0.03	-0.04	0.06	0.17	0.02	-0.15
	(0.04)	(0.08)	(0.10)	(0.11)	(0.10)	(0.14)
Couple with children	0.07	-0.01	0.11	0.06	0.11	-0.52*
	(0.06)	(0.11)	(0.14)	(0.16)	(0.14)	(0.28)
Single parent with one or more children	-0.08	-0.24	-0.13	-0.10	0.11	-0.05
	(0.07)	(0.17)	(0.19)	(0.15)	(0.14)	(0.47)
Patchwork family	0.03	0.08	-0.10	-0.05	0.19	-0.66
	(0.08)	(0.20)	(0.23)	(0.20)	(0.16)	(0.47)
Non-family shared household	0.15**	0.13	0.26*	0.12	0.11	-0.20
	(0.06)	(0.10)	(0.15)	(0.19)	(0.19)	(0.28)
Swiss	0.10**	0.04	0.13	0.16	0.15	0.13
	(0.05)	(0.08)	(0.09)	(0.11)	(0.12)	(0.25)
Agglomeration	0.07**					0.17
	(0.03)					(0.10)
Countryside	0.01		-0.11		0.01	-0.10
	(0.04)		(0.07)		(0.06)	(0.14)
Female	-0.02	-0.04	-0.05	0.06	-0.01	-0.07
	(0.03)	(0.06)	(0.06)	(0.07)	(0.06)	(0.10)
Owner	0.11***	0.22*	0.09	0.02	0.18***	0.01
	(0.04)	(0.12)	(0.08)	(0.08)	(0.07)	(0.10)
cut1	0.23	0.37	0.14	0.47	0.02	-2.57***
	(0.15)	(0.33)	(0.35)	(0.43)	(0.43)	(0.85)
cut2	0.59***	0.75**	0.49	0.81*	0.38	-2.15**
	(0.15)	(0.33)	(0.35)	(0.43)	(0.43)	(0.84)
cut3	0.87***	0.98***	0.75**	1.11***	0.68	-1.78**
	(0.15)	(0.33)	(0.35)	(0.43)	(0.43)	(0.84)
cut4	1.23***	1.31***	1.10***	1.49***	1.05**	-1.32
	(0.15)	(0.33)	(0.35)	(0.43)	(0.43)	(0.84)

Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6735	1761	1430	1206	1519	763
Log-likelihood	-9857.4	-2571.8	-2098.0	-1769.1	-2169.4	-1030.0

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordered Probit estimation

Table 52: Number of devices

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	-0.01***	-0.01*	0.00	-0.02***	-0.02***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Injunctive norms	-0.01***	-0.01	0.00	-0.01	-0.03***	-0.02**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Descriptive norms	0.01*	0.00	0.00	0.01	0.01	0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age (household)	0.00	-0.00	-0.00	0.00	0.00	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Household size	0.01**	0.01	0.01	0.01	0.02	0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Education in years	-0.01***	-0.02***	-0.01**	-0.01***	-0.00	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Income 3'000-4'459	0.06***	0.07**	0.05	0.03	0.04	0.12***
	(0.02)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
Income 4'500-5'999	0.11***	0.14***	0.12***	0.02	0.07*	0.20***
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
Income 6'000-8'999	0.16***	0.19***	0.16***	0.14***	0.11***	0.22***
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
Income 9'000-12'000	0.23***	0.28***	0.21***	0.22***	0.17***	0.31***
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
Income 12'000 or more	0.29***	0.36***	0.25***	0.25***	0.23***	0.34***
	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)
Couple without children	0.14***	0.15***	0.18***	0.20***	0.11***	0.07*
	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
Couple with children	0.22***	0.23***	0.23***	0.29***	0.18***	0.10
	(0.02)	(0.04)	(0.04)	(0.04)	(0.03)	(0.06)
Single parent with one or more children	0.14***	0.12***	0.19***	0.21***	0.12***	-0.08
	(0.02)	(0.04)	(0.05)	(0.04)	(0.04)	(0.13)
Patchwork family	0.24***	0.25***	0.23***	0.30***	0.21***	0.09
	(0.02)	(0.06)	(0.06)	(0.05)	(0.04)	(0.13)
Non-family shared household	0.08***	0.08**	0.09**	0.13**	0.07	0.03
	(0.02)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)
Swiss	0.04***	0.06***	0.04**	-0.03	0.05*	-0.01
	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.06)
Agglomeration	0.07***					0.05**
	(0.01)					(0.02)
Countryside	0.08***		-0.01		0.02	0.06**
	(0.01)		(0.02)		(0.01)	(0.03)
Female	-0.06***	-0.04***	-0.08***	-0.07***	-0.08***	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Owner	0.12***	0.12***	0.09***	0.13***	0.13***	0.16***
	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	2.42***	2.48***	2.40***	2.54***	2.53***	2.78***
	(0.04)	(0.09)	(0.09)	(0.10)	(0.09)	(0.17)

Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7451	1893	1525	1356	1700	921
Log-likelihood	-20652.6	-5132.0	-4205.6	-3746.4	-4762.8	-2498.2

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Poisson estimation

Table 53: Energy efficiency label knowledge: Tv

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.03***	0.03*	0.02	0.07***	0.02	0.04
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Injunctive norms	0.06***	0.06	0.03	0.09**	0.08*	0.03
	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)
Descriptive norms	0.03*	0.02	0.07*	-0.00	0.02	0.10*
	(0.02)	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)
Age (household)	0.00***	0.02**	0.01*	0.01	0.01	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Household size	0.02	0.01	0.07*	0.05	0.01	-0.08
	(0.02)	(0.06)	(0.04)	(0.06)	(0.04)	(0.10)
Education in years	-0.02***	-0.01	-0.02	-0.04*	-0.04**	0.00
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Income 3'000-4'459	0.02	0.15	-0.07	0.12	0.05	-0.36*
	(0.08)	(0.18)	(0.21)	(0.20)	(0.19)	(0.20)
Income 4'500-5'999	-0.08	0.00	-0.37**	0.23	-0.09	-0.49**
	(0.08)	(0.16)	(0.19)	(0.19)	(0.18)	(0.19)
Income 6'000-8'999	-0.08	0.05	-0.35**	0.07	0.10	-0.68***
	(0.07)	(0.15)	(0.18)	(0.18)	(0.17)	(0.20)
Income 9'000-12'000	-0.17**	-0.19	-0.32*	0.06	-0.11	-0.64***
	(0.08)	(0.16)	(0.19)	(0.20)	(0.18)	(0.23)
Income 12'000 or more	-0.20**	-0.16	-0.35*	-0.06	-0.08	-0.73**
	(0.08)	(0.17)	(0.20)	(0.20)	(0.19)	(0.29)
Couple without children	0.09*	0.12	0.07	0.03	0.09	0.40**
	(0.05)	(0.11)	(0.12)	(0.13)	(0.11)	(0.16)
Couple with children	0.04	0.22	-0.17	-0.10	0.04	0.74**
	(0.08)	(0.18)	(0.16)	(0.20)	(0.16)	(0.30)
Single parent with one or more children	0.07	-0.02	-0.07	0.09	0.16	-0.09
	(0.09)	(0.19)	(0.21)	(0.18)	(0.17)	(0.47)
Patchwork family	0.14	0.24	-0.15	-0.03	0.25	0.22
	(0.11)	(0.27)	(0.25)	(0.22)	(0.20)	(0.69)
Non-family shared household	0.06	-0.03	-0.09	0.20	0.46**	0.79***
	(0.08)	(0.15)	(0.19)	(0.24)	(0.23)	(0.27)
Swiss	-0.25***	-0.09	-0.42***	-0.24*	-0.22*	-0.97***
	(0.05)	(0.10)	(0.11)	(0.13)	(0.13)	(0.34)
Agglomeration	0.05					-0.08
	(0.04)					(0.11)
Countryside	0.05		0.03		0.00	-0.02
	(0.04)		(0.08)		(0.07)	(0.13)
Female	-0.37***	-0.40***	-0.49***	-0.23***	-0.43***	-0.18*
	(0.03)	(0.07)	(0.07)	(0.08)	(0.07)	(0.10)
Owner	-0.01	0.01	-0.18**	0.02	-0.02	0.15
	(0.04)	(0.14)	(0.09)	(0.09)	(0.07)	(0.10)
Constant	0.17	-0.73*	0.48	-0.18	0.36	1.31*
	(0.18)	(0.40)	(0.42)	(0.46)	(0.45)	(0.79)

Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6575	1509	1389	1178	1581	868
Log-likelihood	-4381.0	-986.3	-898.2	-776.9	-1034.1	-554.8

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit estimation

Table 54: Energy efficiency label - Tv

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.04***	0.02	0.06***	0.06**	0.04*	0.07**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Injunctive norms	-0.03	-0.06	-0.03	0.01	0.02	-0.10
	(0.02)	(0.05)	(0.05)	(0.05)	(0.04)	(0.07)
Descriptive norms	-0.08***	-0.06	-0.06	-0.18***	-0.03	-0.14*
	(0.02)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)
Age (household)	-0.00**	0.02**	0.01	-0.00	-0.01	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	0.02	0.01	-0.02	-0.06	-0.00	0.24***
	(0.03)	(0.09)	(0.04)	(0.06)	(0.05)	(0.09)
Education in years	0.01	0.03	0.01	-0.03	0.03	-0.01
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Income 3'000-4'459	0.02	0.08	0.24	0.02	-0.24	-0.16
	(0.10)	(0.24)	(0.24)	(0.25)	(0.22)	(0.21)
Income 4'500-5'999	-0.01	0.23	0.37*	-0.23	-0.28	-0.38*
	(0.09)	(0.21)	(0.22)	(0.24)	(0.21)	(0.20)
Income 6'000-8'999	-0.02	-0.07	0.24	-0.05	-0.11	-0.32
	(0.09)	(0.21)	(0.21)	(0.23)	(0.19)	(0.21)
Income 9'000-12'000	0.10	-0.01	0.37*	-0.06	0.00	0.09
	(0.10)	(0.22)	(0.22)	(0.25)	(0.20)	(0.23)
Income 12'000 or more	-0.13	-0.07	-0.15	-0.25	-0.13	-0.58*
	(0.10)	(0.23)	(0.22)	(0.26)	(0.21)	(0.30)
Couple without children	0.02	0.01	0.24*	0.08	-0.01	-0.24
	(0.06)	(0.14)	(0.13)	(0.14)	(0.13)	(0.16)
Couple with children	0.02	-0.10	0.20	0.38*	-0.08	-0.68**
	(0.09)	(0.27)	(0.17)	(0.20)	(0.18)	(0.31)
Single parent with one or more children	-0.03	-0.25	0.13	0.17	-0.01	-0.29
	(0.11)	(0.32)	(0.27)	(0.22)	(0.18)	(0.47)
Patchwork family	0.01	0.40	0.39	-0.14	-0.07	-0.27
	(0.11)	(0.38)	(0.26)	(0.22)	(0.21)	(0.83)
Non-family shared household	-0.06	0.15	0.05	0.04	-0.35	-0.51*
	(0.10)	(0.21)	(0.22)	(0.27)	(0.26)	(0.27)
Swiss	0.10	0.06	0.21*	0.05	0.14	0.11
	(0.06)	(0.12)	(0.12)	(0.14)	(0.16)	(0.24)
Agglomeration	-0.02					-0.13
	(0.05)					(0.13)
Countryside	-0.01		-0.00		0.00	-0.12
	(0.05)		(0.09)		(0.08)	(0.15)
Female	-0.13***	-0.27***	-0.19**	-0.08	-0.09	-0.06
	(0.04)	(0.08)	(0.08)	(0.09)	(0.08)	(0.12)
Owner	-0.08*	0.05	-0.09	0.03	-0.08	-0.08
	(0.04)	(0.15)	(0.11)	(0.10)	(0.08)	(0.12)
cut1	-0.95***	-0.23	-0.18	-1.71***	-0.93*	-2.31***
	(0.20)	(0.50)	(0.49)	(0.57)	(0.49)	(0.82)

cut2	0.10	0.82	0.89*	-0.54	0.18	-1.24
	(0.20)	(0.50)	(0.49)	(0.56)	(0.49)	(0.82)
cut3	0.94***	1.69***	1.74***	0.32	1.04**	-0.34
	(0.20)	(0.50)	(0.50)	(0.56)	(0.49)	(0.82)
cut4	1.71***	2.41***	2.47***	1.17**	1.90***	0.53
	(0.21)	(0.51)	(0.50)	(0.56)	(0.49)	(0.83)
cut5	2.24***	2.90***	2.97***	2.08***	2.47***	1.03
	(0.21)	(0.52)	(0.52)	(0.61)	(0.51)	(0.82)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3478	728	726	636	872	489
Log-likelihood	-4961.9	-1048.2	-1044.4	-859.4	-1205.0	-656.0

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordered Probit

Table 55: Energy efficiency label knowledge - fridge

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.05***	0.04**	0.02	0.07***	0.06***	0.07***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Injunctive norms	0.08***	0.07**	0.07**	0.07*	0.09**	0.14**
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)
Descriptive norms	0.01	-0.01	0.09**	-0.01	-0.01	0.02
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)
Age (household)	0.01***	0.00	0.00	0.01**	0.01**	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Household size	0.04**	0.04	0.08*	0.05	0.05	-0.14
	(0.02)	(0.04)	(0.04)	(0.05)	(0.05)	(0.09)
Education in years	-0.04***	-0.04**	-0.04**	-0.02	-0.05***	0.03
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Income 3'000-4'459	0.12	0.42***	-0.10	-0.03	0.20	-0.26
	(0.07)	(0.14)	(0.18)	(0.18)	(0.19)	(0.19)
Income 4'500-5'999	-0.00	0.16	-0.23	-0.07	-0.01	-0.28
	(0.07)	(0.13)	(0.16)	(0.17)	(0.18)	(0.19)
Income 6'000-8'999	0.02	0.10	-0.16	-0.20	0.20	-0.28
	(0.07)	(0.12)	(0.16)	(0.16)	(0.17)	(0.19)
Income 9'000-12'000	-0.05	-0.01	-0.07	-0.18	-0.05	-0.35
	(0.07)	(0.13)	(0.17)	(0.18)	(0.18)	(0.23)
Income 12'000 or more	-0.04	-0.01	-0.13	-0.28	0.07	-0.31
	(0.08)	(0.14)	(0.18)	(0.18)	(0.19)	(0.30)
Couple without children	0.09**	0.11	-0.08	0.39***	0.01	0.50***
	(0.05)	(0.09)	(0.11)	(0.12)	(0.12)	(0.16)
Couple with children	0.18**	0.25*	0.00	0.28	0.03	0.58*
	(0.07)	(0.14)	(0.15)	(0.18)	(0.17)	(0.31)
Single parent with one or more children	0.12	0.11	-0.24	0.20	0.13	0.03
	(0.08)	(0.18)	(0.21)	(0.17)	(0.17)	(0.39)
Patchwork family	0.26**	-0.12	-0.15	0.47**	0.34	0.80
	(0.10)	(0.24)	(0.24)	(0.22)	(0.22)	(0.65)
Non-family shared household	0.01	-0.01	-0.34**	0.38*	0.48**	0.65**
	(0.07)	(0.12)	(0.17)	(0.22)	(0.23)	(0.28)
Swiss	-0.15***	-0.10	-0.25**	-0.14	0.02	-0.66*
	(0.05)	(0.09)	(0.11)	(0.13)	(0.13)	(0.35)
Agglomeration	0.02					-0.06
	(0.04)					(0.12)

Countryside	0.14***		0.16**		0.05	0.29*
	(0.04)		(0.07)		(0.07)	(0.15)
Female	-0.14***	-0.16***	-0.30***	-0.00	-0.15**	0.04
	(0.03)	(0.06)	(0.07)	(0.08)	(0.07)	(0.11)
Owner	0.44***	0.63***	0.34***	0.44***	0.41***	0.43***
	(0.04)	(0.13)	(0.09)	(0.09)	(0.07)	(0.11)
Constant	-0.41**	-0.23	0.38	-0.52	-0.28	0.59
	(0.17)	(0.35)	(0.40)	(0.44)	(0.45)	(0.83)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7414	1879	1515	1353	1689	911
Log-likelihood	-4613.4	-1230.7	-973.5	-803.3	-961.0	-493.0

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit estimation

Table 56: Energy efficiency label - fridge

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.03***	0.05**	0.01	0.00	0.04**	0.06**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Injunctive norms	-0.02	0.00	-0.02	0.01	-0.06*	0.03
	(0.02)	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)
Descriptive norms	-0.03	-0.07	0.00	-0.07	0.01	0.00
	(0.02)	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)
Age (household)	-0.00	0.01	0.01	-0.00	-0.00	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Household size	-0.01	0.11***	-0.13***	-0.09*	-0.05	0.22***
	(0.02)	(0.04)	(0.04)	(0.05)	(0.04)	(0.08)
Education in years	-0.01	-0.01	-0.01	-0.02	-0.01	0.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Income 3'000-4'459	0.04	0.30*	-0.07	0.08	-0.04	-0.05
	(0.09)	(0.17)	(0.23)	(0.19)	(0.23)	(0.18)
Income 4'500-5'999	0.01	0.37**	0.01	0.04	-0.21	-0.17
	(0.08)	(0.17)	(0.20)	(0.19)	(0.23)	(0.17)
Income 6'000-8'999	-0.10	0.07	-0.13	-0.11	-0.20	-0.21
	(0.08)	(0.16)	(0.19)	(0.18)	(0.22)	(0.17)
Income 9'000-12'000	-0.08	0.15	-0.11	-0.03	-0.19	-0.31
	(0.08)	(0.18)	(0.20)	(0.19)	(0.22)	(0.20)
Income 12'000 or more	-0.26***	-0.02	-0.33	-0.16	-0.35	-0.73***
	(0.09)	(0.19)	(0.21)	(0.20)	(0.23)	(0.24)
Couple without children	-0.05	-0.24**	0.10	-0.07	-0.08	-0.12
	(0.05)	(0.11)	(0.13)	(0.12)	(0.11)	(0.16)
Couple with children	-0.03	-0.44***	0.13	0.17	0.07	-0.26
	(0.07)	(0.14)	(0.17)	(0.18)	(0.16)	(0.30)
Single parent with one or more children	-0.05	-0.27	0.56***	0.02	-0.22	0.09
	(0.09)	(0.23)	(0.20)	(0.17)	(0.18)	(0.44)
Patchwork family	-0.00	-0.24	0.44	0.06	-0.06	-0.43
	(0.11)	(0.41)	(0.28)	(0.21)	(0.19)	(0.50)
Non-family shared household	-0.03	-0.06	0.08	-0.05	-0.11	-0.43*
	(0.09)	(0.14)	(0.22)	(0.26)	(0.22)	(0.25)
Swiss	-0.03	-0.02	0.03	-0.05	-0.03	0.12
	(0.05)	(0.11)	(0.11)	(0.13)	(0.12)	(0.23)
Agglomeration	-0.07					-0.03
	(0.04)					(0.12)

Countryside	-0.07		-0.02		0.01	-0.00
	(0.05)		(0.08)		(0.07)	(0.12)
Female	-0.18***	0.01	-0.02	-0.39***	-0.20***	-0.11
	(0.03)	(0.08)	(0.08)	(0.08)	(0.07)	(0.10)
Owner	-0.25***	-0.10	-0.34***	-0.34***	-0.25***	-0.19*
	(0.04)	(0.14)	(0.09)	(0.08)	(0.07)	(0.10)
cut1	-1.09***	-0.18	-0.84*	-1.82***	-1.38***	-0.44
	(0.18)	(0.43)	(0.44)	(0.46)	(0.44)	(0.74)
cut2	0.05	1.04**	0.33	-0.64	-0.27	0.72
	(0.18)	(0.43)	(0.44)	(0.46)	(0.44)	(0.74)
cut3	0.86***	1.86***	1.18***	0.09	0.61	1.58**
	(0.18)	(0.43)	(0.44)	(0.46)	(0.44)	(0.75)
cut4	1.33***	2.26***	1.76***	0.47	1.16***	2.23***
	(0.18)	(0.43)	(0.45)	(0.46)	(0.45)	(0.76)
cut5	1.58***	2.47***	1.99***	0.70	1.47***	2.61***
	(0.18)	(0.44)	(0.45)	(0.46)	(0.45)	(0.75)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4515	871	849	906	1196	659
Log-likelihood	-6019.2	-1158.0	-1100.8	-1224.0	-1518.0	-859.0

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordered probit estimation

Table 57: Energy efficiency label knowledge - washing machine

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.04***	0.01	0.05***	0.06***	0.04**	0.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Injunctive norms	0.05**	0.03	0.07	0.03	0.05	0.07
	(0.02)	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)
Descriptive norms	0.05**	0.07	0.08**	0.09*	0.02	0.02
	(0.02)	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)
Age (household)	0.01***	0.02**	0.01	-0.00	0.01	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Household size	0.02	-0.00	0.04	0.04	0.02	-0.05
	(0.02)	(0.05)	(0.05)	(0.05)	(0.05)	(0.10)
Education in years	-0.03***	-0.04*	-0.05**	-0.03	-0.04**	-0.00
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Income 3'000-4'459	0.01	0.22	0.17	-0.20	0.01	-0.37*
	(0.09)	(0.21)	(0.22)	(0.23)	(0.20)	(0.22)
Income 4'500-5'999	-0.07	-0.20	0.01	-0.08	0.04	-0.32
	(0.09)	(0.19)	(0.19)	(0.23)	(0.19)	(0.22)
Income 6'000-8'999	-0.06	-0.05	0.09	-0.36*	0.04	-0.42*
	(0.08)	(0.17)	(0.18)	(0.21)	(0.18)	(0.22)
Income 9'000-12'000	-0.16*	-0.14	0.15	-0.27	-0.22	-0.70***
	(0.09)	(0.18)	(0.19)	(0.22)	(0.18)	(0.25)
Income 12'000 or more	-0.19**	-0.22	-0.01	-0.41*	-0.10	-0.57*
	(0.09)	(0.19)	(0.20)	(0.23)	(0.19)	(0.32)
Couple without children	0.13**	0.07	-0.04	0.31**	0.06	0.46***
	(0.05)	(0.13)	(0.13)	(0.14)	(0.12)	(0.17)
Couple with children	0.25***	0.36*	-0.02	0.25	0.22	0.65**
	(0.07)	(0.19)	(0.18)	(0.20)	(0.17)	(0.32)
Single parent with one or more children	0.14	-0.17	-0.06	0.29	0.08	0.55
	(0.09)	(0.23)	(0.23)	(0.20)	(0.18)	(0.40)

Patchwork family	0.32***	0.26	0.00	0.14	0.46**	0.66
	(0.11)	(0.33)	(0.27)	(0.22)	(0.22)	(0.72)
Non-family shared household	0.05	-0.18	0.02	0.36	0.76***	0.33
	(0.08)	(0.17)	(0.22)	(0.25)	(0.25)	(0.27)
Swiss	-0.28***	-0.39***	-0.38***	-0.06	-0.08	-0.22
	(0.06)	(0.12)	(0.12)	(0.15)	(0.14)	(0.31)
Agglomeration	0.02					0.20*
	(0.04)					(0.12)
Countryside	0.08		0.04		0.06	0.25*
	(0.05)		(0.08)		(0.08)	(0.14)
Female	-0.07*	-0.22***	-0.14*	0.10	-0.04	0.05
	(0.04)	(0.08)	(0.08)	(0.09)	(0.07)	(0.11)
Owner	0.40***	0.39***	0.40***	0.39***	0.37***	0.39***
	(0.04)	(0.13)	(0.09)	(0.10)	(0.08)	(0.11)
Constant	-0.10	-0.01	-0.13	-0.05	-0.26	1.12
	(0.19)	(0.45)	(0.45)	(0.52)	(0.47)	(0.87)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5834	1196	1245	1019	1550	771
Log-likelihood	-3735.8	-767.2	-804.6	-633.5	-940.3	-463.3

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit estimation

Table 58: Energy efficiency label - washing machine

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.03***	0.04	0.06**	0.01	0.06***	0.02
	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Injunctive norms	-0.04	-0.05	-0.11**	0.07	-0.05	0.03
	(0.02)	(0.05)	(0.05)	(0.05)	(0.04)	(0.08)
Descriptive norms	0.00	0.00	0.05	-0.11*	0.07	-0.08
	(0.02)	(0.05)	(0.05)	(0.06)	(0.04)	(0.07)
Age (household)	-0.00	0.01	-0.00	-0.01	-0.00	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	-0.01	0.02	-0.01	-0.12**	-0.01	-0.04
	(0.02)	(0.05)	(0.06)	(0.06)	(0.04)	(0.10)
Education in years	0.01	0.02	0.03	-0.04	0.02	0.01
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Income 3'000-4'459	0.08	0.09	0.07	0.21	0.20	-0.02
	(0.11)	(0.23)	(0.26)	(0.26)	(0.26)	(0.21)
Income 4'500-5'999	0.02	0.24	0.19	0.00	0.06	-0.14
	(0.10)	(0.22)	(0.21)	(0.26)	(0.23)	(0.21)
Income 6'000-8'999	-0.07	0.07	-0.06	-0.10	0.00	-0.16
	(0.09)	(0.20)	(0.20)	(0.23)	(0.22)	(0.21)
Income 9'000-12'000	0.04	0.18	0.13	0.11	-0.02	-0.02
	(0.10)	(0.21)	(0.22)	(0.25)	(0.23)	(0.26)
Income 12'000 or more	-0.19*	-0.08	0.00	-0.25	-0.16	-0.16
	(0.10)	(0.22)	(0.23)	(0.26)	(0.23)	(0.29)
Couple without children	-0.07	-0.27*	-0.01	0.03	0.00	-0.03
	(0.06)	(0.14)	(0.16)	(0.14)	(0.13)	(0.18)
Couple with children	-0.05	-0.28	-0.09	0.09	0.14	0.05
	(0.08)	(0.21)	(0.22)	(0.21)	(0.16)	(0.30)
Single parent with one or more children	0.06	-0.46*	0.51**	0.05	0.17	0.71*

	(0.10)	(0.27)	(0.25)	(0.21)	(0.18)	(0.38)
Patchwork family	0.02	0.41	0.15	-0.17	0.09	0.42
	(0.11)	(0.39)	(0.32)	(0.25)	(0.21)	(0.87)
Non-family shared household	0.10	-0.06	-0.08	0.24	0.44**	-0.01
	(0.10)	(0.21)	(0.24)	(0.30)	(0.22)	(0.26)
Swiss	0.04	0.08	-0.08	0.18	0.03	0.29
	(0.06)	(0.12)	(0.13)	(0.17)	(0.15)	(0.22)
Agglomeration	-0.09*					0.05
	(0.05)					(0.12)
Countryside	-0.02		0.16*		-0.01	0.16
	(0.05)		(0.09)		(0.08)	(0.14)
Female	-0.19***	-0.02	0.05	-0.43***	-0.24***	-0.14
	(0.04)	(0.10)	(0.09)	(0.10)	(0.08)	(0.12)
Owner	-0.19***	-0.17	-0.35***	-0.06	-0.20**	-0.18
	(0.04)	(0.15)	(0.10)	(0.10)	(0.08)	(0.12)
2000-2009	0.40***	0.53***	0.39**	0.44**	0.27**	1.05***
	(0.06)	(0.18)	(0.15)	(0.17)	(0.12)	(0.22)
1990-1999	0.32***	0.34*	0.46***	0.25	0.31***	0.73***
	(0.07)	(0.19)	(0.13)	(0.19)	(0.12)	(0.24)
1980-1989	0.45***	0.39**	0.57***	0.35*	0.32**	1.29***
	(0.07)	(0.18)	(0.17)	(0.18)	(0.13)	(0.21)
1970-1979	0.45***	0.40**	0.50***	0.57***	0.47***	0.91***
	(0.07)	(0.18)	(0.15)	(0.19)	(0.15)	(0.20)
1960-1969	0.40***	0.48**	0.42**	0.28	0.29*	0.96***
	(0.08)	(0.20)	(0.20)	(0.21)	(0.16)	(0.26)
Before 1960	0.31***	0.23	0.29**	0.43***	0.28**	1.05***
	(0.06)	(0.15)	(0.13)	(0.14)	(0.12)	(0.21)
do not know	0.13	0.31	-0.58**	-1.46*	0.70***	1.20***
	(0.17)	(0.27)	(0.29)	(0.75)	(0.24)	(0.28)
cut1	-0.39*	0.20	0.04	-1.55**	0.01	-0.50
	(0.22)	(0.53)	(0.51)	(0.60)	(0.54)	(0.91)
cut2	0.68***	1.18**	1.27**	-0.49	1.15**	0.58
	(0.22)	(0.53)	(0.51)	(0.60)	(0.54)	(0.91)
cut3	1.50***	2.09***	2.10***	0.46	2.00***	1.32
	(0.22)	(0.53)	(0.51)	(0.60)	(0.54)	(0.91)
cut4	2.22***	2.83***	2.88***	1.12*	2.76***	2.13**
	(0.22)	(0.53)	(0.51)	(0.61)	(0.55)	(0.92)
cut5	2.70***	3.20***	3.44***	1.45**	3.40***	2.83***
	(0.23)	(0.55)	(0.51)	(0.61)	(0.59)	(0.95)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3465	583	695	632	1025	509
Log-likelihood	-4712.9	-813.8	-893.6	-828.1	-1314.6	-699.1

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordered probit estimation

Table 59: Energy efficiency label knowledge - dishwasher

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.04***	-0.00	0.04**	0.07***	0.06***	0.02
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Injunctive norms	0.05***	0.02	0.05	0.04	0.09**	0.03
	(0.02)	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)
Descriptive norms	0.03	0.07*	0.10**	-0.01	-0.03	-0.02
	(0.02)	(0.04)	(0.04)	(0.05)	(0.04)	(0.07)

Age (household)	0.01***	0.01	0.01	0.01	0.01*	-0.02*
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Household size	0.06***	0.08	0.08	0.08	0.04	0.00
	(0.02)	(0.06)	(0.05)	(0.06)	(0.05)	(0.11)
Education in years	-0.04***	-0.03	-0.05***	-0.05**	-0.05***	0.00
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Income 3'000-4'459	0.02	0.21	-0.14	0.16	-0.30	-0.15
	(0.10)	(0.20)	(0.22)	(0.24)	(0.23)	(0.22)
Income 4'500-5'999	-0.03	0.07	-0.28	0.07	-0.16	-0.25
	(0.09)	(0.18)	(0.20)	(0.23)	(0.22)	(0.22)
Income 6'000-8'999	-0.00	0.10	-0.22	0.07	-0.14	-0.24
	(0.08)	(0.17)	(0.19)	(0.21)	(0.21)	(0.22)
Income 9'000-12'000	-0.11	-0.11	-0.19	0.03	-0.32	-0.42*
	(0.09)	(0.18)	(0.20)	(0.23)	(0.21)	(0.25)
Income 12'000 or more	-0.11	-0.08	-0.24	-0.10	-0.33	-0.12
	(0.09)	(0.18)	(0.21)	(0.23)	(0.22)	(0.32)
Couple without children	0.06	-0.02	-0.07	0.42***	-0.02	0.35**
	(0.05)	(0.11)	(0.12)	(0.13)	(0.12)	(0.17)
Couple with children	0.07	-0.11	-0.08	0.22	-0.02	0.76**
	(0.08)	(0.18)	(0.18)	(0.19)	(0.16)	(0.36)
Single parent with one or more children	0.12	-0.14	-0.29	0.36*	0.14	-0.28
	(0.09)	(0.22)	(0.23)	(0.19)	(0.18)	(0.46)
Patchwork family	0.16	-0.36	-0.02	0.29	0.22	0.76
	(0.11)	(0.28)	(0.26)	(0.22)	(0.21)	(0.67)
Non-family shared household	0.07	-0.19	-0.01	0.56**	0.78***	0.53*
	(0.08)	(0.15)	(0.20)	(0.26)	(0.25)	(0.28)
Swiss	-0.20***	-0.26***	-0.30***	-0.02	-0.14	-0.18
	(0.06)	(0.10)	(0.11)	(0.14)	(0.14)	(0.32)
Agglomeration	0.01					0.15
	(0.04)					(0.12)
Countryside	0.10**		0.19**		0.04	0.13
	(0.05)		(0.08)		(0.07)	(0.14)
Female	-0.11***	-0.30***	-0.16**	0.09	-0.07	0.11
	(0.03)	(0.07)	(0.07)	(0.09)	(0.07)	(0.11)
Owner	0.42***	0.69***	0.37***	0.30***	0.49***	0.31***
	(0.04)	(0.13)	(0.09)	(0.09)	(0.07)	(0.11)
Constant	-0.20	-0.31	0.14	-0.37	-0.06	1.32
	(0.19)	(0.42)	(0.43)	(0.51)	(0.48)	(0.82)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6374	1508	1392	1081	1558	775
Log-likelihood	-4156.4	-956.0	-907.6	-691.4	-975.9	-482.3

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit estimation

Table 60: Energy efficiency label - dishwasher

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.01	0.02	0.02	0.02	0.07**	-0.00
	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
Injunctive norms	-0.03	-0.05	-0.03	-0.01	-0.15**	-0.02
	(0.02)	(0.05)	(0.06)	(0.04)	(0.07)	(0.05)
Descriptive norms	-0.02	-0.01	-0.11*	0.02	0.09	-0.05
	(0.02)	(0.05)	(0.06)	(0.04)	(0.07)	(0.05)

Age (household)	-0.00**	0.00	-0.01	-0.01	0.01	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	-0.01	0.09*	-0.09	-0.01	0.17	0.03
	(0.02)	(0.05)	(0.05)	(0.05)	(0.11)	(0.07)
Education in years	-0.00	0.00	-0.00	-0.01	-0.01	0.03
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Income 3'000-4'459	0.28**	0.01	0.38	0.10	0.73***	0.11
	(0.11)	(0.27)	(0.35)	(0.28)	(0.24)	(0.25)
Income 4'500-5'999	0.25**	0.21	0.13	0.24	0.46**	0.27
	(0.11)	(0.24)	(0.35)	(0.26)	(0.23)	(0.24)
Income 6'000-8'999	0.18*	0.03	0.06	0.26	0.46**	0.00
	(0.11)	(0.22)	(0.33)	(0.25)	(0.23)	(0.23)
Income 9'000-12'000	0.24**	0.17	0.07	0.18	0.61**	0.22
	(0.11)	(0.23)	(0.35)	(0.25)	(0.26)	(0.23)
Income 12'000 or more	0.03	-0.07	-0.09	-0.00	0.26	-0.01
	(0.11)	(0.26)	(0.35)	(0.26)	(0.32)	(0.24)
Couple without children	0.05	-0.08	0.17	-0.08	-0.14	0.04
	(0.06)	(0.15)	(0.15)	(0.13)	(0.18)	(0.14)
Couple with children	-0.07	-0.48**	0.32	-0.07	-0.50	-0.35
	(0.08)	(0.19)	(0.20)	(0.18)	(0.33)	(0.24)
Single parent with one or more children	-0.04	-0.10	0.10	-0.07	0.07	-0.10
	(0.10)	(0.26)	(0.21)	(0.19)	(0.33)	(0.26)
Patchwork family	-0.00	-0.50**	0.12	0.09	-0.45*	-0.40
	(0.12)	(0.25)	(0.24)	(0.23)	(0.26)	(0.43)
Non-family shared household	-0.01	-0.44**	0.04	0.17	-0.56*	-0.01
	(0.10)	(0.21)	(0.29)	(0.23)	(0.31)	(0.20)
Swiss	-0.01	0.03	-0.18	-0.09	-0.16	0.08
	(0.06)	(0.13)	(0.16)	(0.15)	(0.25)	(0.13)
Agglomeration	-0.06				0.06	
	(0.05)				(0.13)	
Countryside	-0.04	-0.19*		0.16**	-0.09	
	(0.05)	(0.10)		(0.08)	(0.15)	
Female	-0.25***	-0.16*	-0.36***	-0.24***	-0.32***	-0.16*
	(0.04)	(0.09)	(0.09)	(0.08)	(0.12)	(0.09)
Owner	-0.16***	-0.33***	-0.09	-0.27***	0.11	-0.10
	(0.04)	(0.10)	(0.10)	(0.08)	(0.13)	(0.14)
Accommodation 2000-2009	0.45***	0.42***	0.37**	0.30***	0.68***	0.57***
	(0.06)	(0.15)	(0.16)	(0.12)	(0.21)	(0.19)
Accommodation 1990-1999	0.38***	0.49***	0.27	0.31***	0.35	0.53***
	(0.07)	(0.15)	(0.17)	(0.12)	(0.26)	(0.17)
Accommodation 1980-1989	0.45***	0.58***	0.52***	0.11	0.70***	0.57***
	(0.07)	(0.15)	(0.17)	(0.14)	(0.21)	(0.15)
Accommodation 1970-1979	0.53***	0.32**	0.75***	0.39***	0.61***	0.78***
	(0.07)	(0.15)	(0.19)	(0.14)	(0.21)	(0.17)
Accommodation 1960-1969	0.41***	0.38**	0.28	0.50***	0.43*	0.50***
	(0.08)	(0.17)	(0.19)	(0.18)	(0.26)	(0.18)
Accommodation before 1960	0.38***	0.37***	0.37***	0.28**	0.48**	0.57***
	(0.06)	(0.14)	(0.14)	(0.12)	(0.21)	(0.13)
Accommodation do not know	-0.05	-1.01**	0.69*	0.09	0.89***	0.06
	(0.16)	(0.42)	(0.41)	(0.24)	(0.31)	(0.24)
cut1	-0.70***	-0.64	-1.48**	-0.95*	0.76	0.07
	(0.22)	(0.54)	(0.67)	(0.53)	(0.85)	(0.53)
cut2	0.38*	0.53	-0.40	0.13	1.94**	1.17**
	(0.22)	(0.54)	(0.66)	(0.53)	(0.85)	(0.53)

cut3	1.24***	1.39**	0.47	1.01*	2.79***	2.16***
	(0.22)	(0.54)	(0.66)	(0.53)	(0.86)	(0.53)
cut4	1.89***	2.04***	1.13*	1.69***	3.80***	2.63***
	(0.22)	(0.54)	(0.66)	(0.54)	(0.87)	(0.54)
cut5	2.32***	2.61***	1.52**	2.18***	4.19***	3.04***
	(0.22)	(0.55)	(0.67)	(0.54)	(0.87)	(0.54)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3390	687	627	953	491	608
Log-likelihood	-4630.6	-899.5	-845.6	-1265.8	-636.3	-832.4

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Ordered probit estimation

Table 61: Electricity mix changed to greener mix

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.09***	0.09***	0.08***	0.12***	0.07***	0.09***
	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Injunctive norms	0.13***	0.15***	0.12**	0.19***	0.11**	0.15**
	(0.02)	(0.04)	(0.05)	(0.05)	(0.05)	(0.07)
Descriptive norms	-0.09***	-0.09**	-0.11**	-0.18***	-0.11**	0.04
	(0.02)	(0.04)	(0.05)	(0.05)	(0.05)	(0.07)
Age (household)	0.00**	-0.00	0.02**	-0.01	-0.00	0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	0.05*	0.07	0.09*	0.04	0.02	-0.28
	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)	(0.17)
Education in years	0.05***	0.03	0.07**	0.09***	0.05**	0.06**
	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Income 3'000-4'459	0.04	0.03	-0.19	0.10	-0.16	0.20
	(0.10)	(0.19)	(0.26)	(0.22)	(0.25)	(0.24)
Income 4'500-5'999	0.08	0.18	-0.38	-0.16	0.12	0.40*
	(0.09)	(0.17)	(0.24)	(0.21)	(0.23)	(0.23)
Income 6'000-8'999	0.23***	0.30*	-0.17	0.29	0.23	0.29
	(0.09)	(0.16)	(0.22)	(0.19)	(0.22)	(0.24)
Income 9'000-12'000	0.26***	0.32*	-0.16	0.20	0.31	0.29
	(0.09)	(0.17)	(0.23)	(0.21)	(0.23)	(0.27)
Income 12'000 or more	0.27***	0.48***	-0.34	0.13	0.33	-0.16
	(0.10)	(0.17)	(0.24)	(0.22)	(0.23)	(0.35)
Couple without children	-0.13**	-0.23**	-0.02	0.07	-0.20	0.42*
	(0.06)	(0.11)	(0.16)	(0.13)	(0.13)	(0.23)
Couple with children	-0.25***	-0.38**	-0.22	-0.17	-0.47**	0.76*
	(0.09)	(0.17)	(0.21)	(0.20)	(0.20)	(0.42)
Single parent with one or more children	-0.23**	-0.42*	-0.52	-0.19	-0.21	
	(0.11)	(0.24)	(0.36)	(0.18)	(0.22)	
Patchwork family	0.01	-0.23	-0.26	0.21	-0.11	1.36**
	(0.12)	(0.26)	(0.36)	(0.24)	(0.23)	(0.67)
Non-family shared household	-0.27***	-0.46***	-0.15	0.19	-0.49*	0.35
	(0.10)	(0.16)	(0.24)	(0.23)	(0.29)	(0.34)
Swiss	0.17***	0.18*	0.19	0.12	0.15	0.48
	(0.07)	(0.11)	(0.16)	(0.14)	(0.16)	(0.37)
Agglomeration	-0.26***					-0.38***
	(0.05)					(0.13)
Countryside	-0.25***		-0.04		0.03	-0.32**
	(0.05)		(0.10)		(0.09)	(0.16)

Female	0.02	-0.05	-0.22**	0.24***	-0.03	0.22*
	(0.04)	(0.07)	(0.09)	(0.09)	(0.08)	(0.13)
Owner	0.06	0.00	0.05	-0.07	0.13	0.06
	(0.05)	(0.14)	(0.12)	(0.10)	(0.09)	(0.12)
Constant	-2.63***	-2.23***	-3.28***	-2.60***	-2.15***	-4.27***
	(0.22)	(0.46)	(0.56)	(0.50)	(0.58)	(0.92)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6947	1711	1372	1253	1622	847
Log-likelihood	-3053.7	-788.9	-465.1	-642.6	-661.4	-369.2

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit estimation

Table 62: Switching off devices (often to almost never) – average over tv, tv box, coffee machine, computer, internet router, smartphone

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	0.00	0.01	0.01	-0.03*	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Injunctive norms	-0.08***	-0.08***	-0.08***	-0.11***	-0.07***	-0.08**
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
Descriptive norms	0.01	0.01	0.00	0.03	0.03	-0.04
	(0.01)	(0.02)	(0.03)	(0.03)	(0.02)	(0.04)
Age	-0.01***	-0.00	0.00	-0.01**	-0.01*	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Household size	-0.02*	0.03	-0.08***	-0.03	0.01	0.02
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)
Education in years	-0.01	-0.01	-0.03**	0.00	-0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income 3'000-4'459	0.00	0.13	0.21	-0.13	-0.30**	0.12
	(0.05)	(0.09)	(0.14)	(0.12)	(0.13)	(0.10)
Income 4'500-5'999	0.03	0.18**	0.08	0.05	-0.22*	0.08
	(0.05)	(0.09)	(0.12)	(0.12)	(0.13)	(0.10)
Income 6'000-8'999	0.14***	0.21**	0.22*	0.16	-0.08	0.21**
	(0.05)	(0.08)	(0.11)	(0.11)	(0.12)	(0.10)
Income 9'000-12'000	0.21***	0.23**	0.27**	0.16	0.04	0.35***
	(0.05)	(0.09)	(0.12)	(0.12)	(0.12)	(0.12)
Income 12'000 or more	0.33***	0.32***	0.36***	0.25**	0.21*	0.55***
	(0.05)	(0.09)	(0.12)	(0.12)	(0.12)	(0.15)
Couple without children	-0.10***	-0.10*	0.01	-0.05	-0.17**	-0.20**
	(0.03)	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)
Couple with children	-0.08*	-0.24***	0.14	-0.03	-0.21**	-0.27**
	(0.04)	(0.09)	(0.09)	(0.11)	(0.08)	(0.12)
Single parent with one or more children	0.00	-0.08	0.01	0.21**	-0.06	-0.22
	(0.05)	(0.11)	(0.12)	(0.10)	(0.11)	(0.24)
Patchwork family	0.03	-0.14	0.38***	0.08	-0.13	-0.17
	(0.06)	(0.19)	(0.14)	(0.14)	(0.11)	(0.32)
Non-family shared household	-0.04	-0.01	0.08	-0.03	-0.16	-0.19
	(0.05)	(0.08)	(0.12)	(0.12)	(0.13)	(0.15)
Swiss	-0.12***	-0.07	-0.11	-0.26***	-0.06	-0.31**
	(0.03)	(0.06)	(0.07)	(0.09)	(0.07)	(0.14)
Agglomeration	0.00					-0.04
	(0.02)					(0.06)

Countryside	0.01		0.08*		-0.05	-0.11
	(0.03)		(0.05)		(0.05)	(0.07)
Female	-0.12***	-0.03	-0.08*	-0.21***	-0.18***	-0.10
	(0.02)	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)
Owner	-0.09***	-0.12	-0.14***	0.03	-0.09*	-0.11*
	(0.02)	(0.08)	(0.05)	(0.05)	(0.05)	(0.06)
Constant	3.53***	2.97***	3.26***	3.58***	3.31***	4.52***
	(0.11)	(0.25)	(0.27)	(0.30)	(0.31)	(0.47)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6447	1587	1287	1190	1490	852
R-squared	0.13	0.05	0.07	0.10	0.08	0.12

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. OLS estimation

Table 63: Weekly usage of appliances (ln)

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	-0.01***	-0.02**	-0.00	-0.02	-0.02**	-0.02
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Injunctive norms	-0.02*	-0.02	-0.03	-0.03	-0.01	-0.00
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Descriptive norms	0.00	-0.01	0.03	0.03	-0.01	-0.03
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Age (household)	-0.00	-0.00	-0.00	-0.01*	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Household size	0.06***	0.01	0.05	0.13***	0.15***	0.15***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.05)
Education in years	-0.02***	-0.03***	-0.02*	-0.02	-0.01	0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income 3'000-4'459	0.01	-0.05	-0.09	0.11	-0.02	0.15
	(0.05)	(0.10)	(0.11)	(0.13)	(0.11)	(0.11)
Income 4'500-5'999	0.02	-0.04	0.01	0.09	-0.05	0.09
	(0.04)	(0.09)	(0.10)	(0.12)	(0.10)	(0.11)
Income 6'000-8'999	0.15***	0.15*	0.09	0.28**	0.04	0.22**
	(0.04)	(0.09)	(0.10)	(0.12)	(0.09)	(0.10)
Income 9'000-12'000	0.22***	0.22**	0.17*	0.29**	0.11	0.35***
	(0.05)	(0.09)	(0.10)	(0.13)	(0.10)	(0.12)
Income 12'000 or more	0.30***	0.36***	0.19*	0.45***	0.17*	0.42***
	(0.05)	(0.10)	(0.10)	(0.13)	(0.10)	(0.16)
Couple without children	0.43***	0.37***	0.45***	0.37***	0.39***	0.32***
	(0.03)	(0.06)	(0.07)	(0.07)	(0.06)	(0.08)
Couple with children	0.82***	0.86***	0.85***	0.65***	0.68***	0.29*
	(0.06)	(0.08)	(0.11)	(0.09)	(0.09)	(0.18)
Single parent with one or more children	0.53***	0.61***	0.62***	0.45***	0.45***	-0.57***
	(0.06)	(0.11)	(0.12)	(0.10)	(0.09)	(0.21)
Patchwork family	0.66***	0.65***	0.70***	0.53***	0.53***	-0.10
	(0.07)	(0.14)	(0.15)	(0.11)	(0.10)	(0.18)
Non-family shared household	0.28***	0.27***	0.36***	0.20*	0.28**	0.11
	(0.05)	(0.08)	(0.11)	(0.12)	(0.13)	(0.12)
Swiss	-0.06*	-0.10*	-0.13**	-0.07	0.06	-0.04
	(0.03)	(0.05)	(0.06)	(0.07)	(0.07)	(0.16)
Agglomeration	0.11***					0.05
	(0.02)					(0.06)

Countryside	0.14***		0.02		0.04	0.10
	(0.02)		(0.04)		(0.04)	(0.07)
Female	-0.01	-0.08**	0.01	0.03	-0.01	0.03
	(0.02)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)
Owner	0.17***	0.23***	0.13***	0.19***	0.14***	0.21***
	(0.02)	(0.07)	(0.05)	(0.04)	(0.04)	(0.05)
Constant	1.26***	1.79***	1.39***	1.19***	1.15***	1.18**
	(0.10)	(0.21)	(0.23)	(0.26)	(0.23)	(0.46)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6848	1638	1461	1196	1650	857
R-squared	0.33	0.26	0.29	0.40	0.39	0.24

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. OLS estimation

Table 64: Daily usage of devices (ln)

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	-0.02***	-0.01	-0.01	-0.03**	-0.02**	-0.03***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Injunctive norms	-0.04***	-0.04**	-0.03	-0.04*	-0.04**	-0.01
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Descriptive norms	-0.00	0.02	0.00	-0.02	-0.01	-0.04
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Age (household)	0.01***	0.01	0.01***	0.01*	0.00	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Household size	0.05***	0.03	0.07**	0.04	0.05**	0.00
	(0.01)	(0.03)	(0.04)	(0.03)	(0.02)	(0.04)
Education in years	-0.02***	-0.04***	-0.02**	-0.02*	-0.00	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income 3'000-4'459	-0.19***	-0.19**	-0.21*	-0.20**	-0.30***	0.02
	(0.04)	(0.09)	(0.13)	(0.10)	(0.10)	(0.08)
Income 4'500-5'999	-0.19***	-0.14*	-0.25**	-0.24***	-0.41***	0.08
	(0.04)	(0.08)	(0.11)	(0.09)	(0.10)	(0.08)
Income 6'000-8'999	-0.27***	-0.29***	-0.35***	-0.30***	-0.44***	0.07
	(0.04)	(0.07)	(0.11)	(0.09)	(0.09)	(0.08)
Income 9'000-12'000	-0.25***	-0.23***	-0.40***	-0.27***	-0.42***	0.14
	(0.04)	(0.08)	(0.11)	(0.10)	(0.10)	(0.10)
Income 12'000 or more	-0.20***	-0.24***	-0.33***	-0.26**	-0.35***	0.04
	(0.04)	(0.09)	(0.12)	(0.10)	(0.10)	(0.13)
Couple without children	0.20***	0.19***	0.26***	0.28***	0.26***	0.17**
	(0.03)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)
Couple with children	0.21***	0.13	0.12	0.34***	0.24***	0.25*
	(0.04)	(0.09)	(0.11)	(0.10)	(0.08)	(0.13)
Single parent with one or more children	0.17***	0.14	0.23**	0.18*	0.11	0.19
	(0.04)	(0.11)	(0.11)	(0.09)	(0.09)	(0.27)
Patchwork family	0.26***	0.25	0.30*	0.27**	0.27**	0.06
	(0.06)	(0.19)	(0.16)	(0.12)	(0.11)	(0.20)
Non-family shared household	0.15***	0.23***	0.15	0.16	0.06	0.08
	(0.04)	(0.07)	(0.12)	(0.12)	(0.12)	(0.12)
Swiss	-0.12***	-0.15***	-0.06	-0.16**	-0.21***	0.02
	(0.03)	(0.05)	(0.06)	(0.07)	(0.07)	(0.12)
Agglomeration	0.02					-0.00
	(0.02)					(0.05)

Countryside	0.00		-0.02		0.01	-0.05
	(0.02)		(0.04)		(0.04)	(0.06)
Female	-0.14***	-0.15***	-0.15***	-0.21***	-0.10***	-0.03
	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Owner	0.01	0.09	-0.01	-0.04	0.01	-0.05
	(0.02)	(0.08)	(0.05)	(0.05)	(0.04)	(0.05)
Constant	2.29***	2.53***	2.07***	2.56***	2.51***	2.70***
	(0.10)	(0.22)	(0.24)	(0.24)	(0.25)	(0.35)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7412	1876	1519	1352	1694	918
R-squared	0.07	0.08	0.07	0.11	0.09	0.09

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. OLS estimation

Table 65: Electricity costs (ln)

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	-0.01	-0.02	-0.00	-0.00	-0.02	-0.00
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Injunctive norms	-0.02*	-0.04	0.02	-0.03	-0.03	-0.01
	(0.01)	(0.04)	(0.04)	(0.03)	(0.02)	(0.03)
Descriptive norms	-0.01	-0.05	-0.03	-0.02	0.03	0.01
	(0.01)	(0.04)	(0.04)	(0.03)	(0.02)	(0.03)
Age (household)	0.01***	-0.01	0.03***	-0.00	0.00	0.00
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Household size	0.04**	0.12***	0.06	0.08**	-0.01	0.10
	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.07)
Education in years	-0.01	-0.01	0.02	-0.01	-0.02*	-0.00
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Income 3'000-4'459	0.13*	-0.09	0.34	-0.03	-0.17	0.36***
	(0.07)	(0.25)	(0.22)	(0.12)	(0.12)	(0.12)
Income 4'500-5'999	0.11	0.14	0.12	-0.06	-0.17	0.16
	(0.07)	(0.23)	(0.21)	(0.12)	(0.11)	(0.12)
Income 6'000-8'999	0.06	0.03	0.02	-0.05	-0.24**	0.17
	(0.07)	(0.22)	(0.19)	(0.11)	(0.10)	(0.12)
Income 9'000-12'000	0.05	0.06	-0.11	-0.07	-0.25**	0.15
	(0.07)	(0.22)	(0.20)	(0.12)	(0.11)	(0.13)
Income 12'000 or more	0.11	0.10	0.05	0.01	-0.22*	0.27
	(0.07)	(0.23)	(0.21)	(0.13)	(0.11)	(0.19)
Couple without children	0.17***	0.02	0.18	0.11	0.42***	0.07
	(0.04)	(0.11)	(0.13)	(0.09)	(0.07)	(0.10)
Couple with children	0.29***	0.02	0.29*	0.07	0.59***	0.18
	(0.07)	(0.14)	(0.16)	(0.13)	(0.10)	(0.18)
Single parent with one or more children	0.16**	-0.00	-0.47*	-0.03	0.42***	-0.11
	(0.08)	(0.34)	(0.27)	(0.15)	(0.12)	(0.19)
Patchwork family	0.36***	-0.17	0.28	0.37***	0.55***	0.61***
	(0.09)	(0.31)	(0.28)	(0.13)	(0.12)	(0.20)
Non-family shared household	0.11	-0.08	0.26	0.04	0.28	0.07
	(0.07)	(0.16)	(0.21)	(0.12)	(0.20)	(0.13)
Swiss	0.08	0.04	-0.05	-0.02	0.17*	0.13
	(0.05)	(0.10)	(0.13)	(0.10)	(0.09)	(0.13)
Agglomeration	0.05*					-0.01
	(0.03)					(0.06)

Countryside	0.15***		0.02		0.08	0.08
	(0.03)		(0.08)		(0.05)	(0.08)
Female	-0.08***	-0.08	-0.05	-0.10**	-0.12***	0.03
	(0.02)	(0.07)	(0.07)	(0.05)	(0.05)	(0.06)
Owner	0.20***	0.45***	0.25**	0.24***	0.11*	0.15**
	(0.03)	(0.15)	(0.12)	(0.07)	(0.06)	(0.06)
Accommodation 2000-2009	0.13***	0.06	0.14	0.05	0.12*	0.31***
	(0.05)	(0.15)	(0.11)	(0.10)	(0.07)	(0.12)
Accommodation 1990-1999	0.12**	-0.06	0.21	0.04	0.22***	0.10
	(0.05)	(0.13)	(0.13)	(0.11)	(0.08)	(0.11)
Accommodation 1980-1989	0.24***	0.04	0.30**	0.24**	0.14	0.43***
	(0.05)	(0.14)	(0.12)	(0.10)	(0.09)	(0.11)
Accommodation 1970-1979	0.17***	-0.02	0.06	0.20*	0.19**	0.29***
	(0.05)	(0.12)	(0.15)	(0.11)	(0.09)	(0.10)
Accommodation 1960-1969	0.12**	-0.12	0.05	0.13	0.21**	0.30**
	(0.06)	(0.14)	(0.16)	(0.13)	(0.10)	(0.13)
Accommodation before 1960	0.21***	-0.04	0.11	0.15	0.34***	0.34***
	(0.04)	(0.11)	(0.12)	(0.09)	(0.08)	(0.11)
Accommodation do not know	0.29**	0.20	0.02	0.18	0.48***	0.11
	(0.12)	(0.19)	(0.35)	(0.29)	(0.14)	(0.17)
Accommodation size (ln)	0.27***	0.44***	0.30**	0.18*	0.29***	0.25**
	(0.05)	(0.13)	(0.12)	(0.10)	(0.07)	(0.13)
Number of rooms	0.04**	0.07	0.02	0.06	-0.04	0.05
	(0.02)	(0.04)	(0.05)	(0.04)	(0.03)	(0.04)
Number of bathrooms	0.05**	-0.07	-0.01	0.10*	0.04	0.11**
	(0.02)	(0.08)	(0.06)	(0.05)	(0.04)	(0.04)
Number of other/garages	0.02**	0.07*	-0.02	0.02	0.02	0.03
	(0.01)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
Flat in a building with less than 5 flats	-0.13***	-0.08	-0.01	-0.17*	-0.14*	-0.23**
	(0.04)	(0.13)	(0.13)	(0.09)	(0.08)	(0.09)
Flat in a building with 5 to 10 flats	-0.22***	-0.13	-0.13	-0.20***	-0.28***	-0.33***
	(0.04)	(0.10)	(0.11)	(0.07)	(0.07)	(0.08)
Flat in a building with more than 10 flats	-0.19***	-0.00	-0.13	-0.23***	-0.26***	-0.28***
	(0.04)	(0.11)	(0.12)	(0.08)	(0.10)	(0.09)
Solar-thermal yes	-0.05	-0.13	0.11	-0.00	-0.12*	-0.07
	(0.04)	(0.14)	(0.15)	(0.08)	(0.07)	(0.09)
Photovoltaic yes	-0.26***	-0.07	-0.44***	-0.11	-0.24***	-0.27**
	(0.05)	(0.14)	(0.16)	(0.10)	(0.08)	(0.13)
Electricity warm water yes	0.20***	0.24***	0.24**	0.16**	0.25***	0.13*
	(0.03)	(0.09)	(0.10)	(0.07)	(0.05)	(0.07)
Electricity heating yes	0.19***	-0.24**	0.02	0.26***	0.31***	0.46***
	(0.04)	(0.12)	(0.10)	(0.09)	(0.06)	(0.07)
Minergie yes	-0.01	-0.08	-0.06	-0.12	0.05	0.11
	(0.04)	(0.11)	(0.11)	(0.09)	(0.07)	(0.07)
Minergie do not know	0.06	-0.17	0.16	0.07	0.02	0.14*
	(0.04)	(0.12)	(0.12)	(0.08)	(0.08)	(0.08)
Electricity price (ln)	0.04***	0.05	0.07*	0.05*	0.05*	0.01
	(0.01)	(0.05)	(0.04)	(0.03)	(0.02)	(0.03)
Constant	3.98***	4.32***	3.02***	4.76***	4.73***	3.75***
	(0.24)	(0.64)	(0.78)	(0.47)	(0.43)	(0.67)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3243	520	458	683	947	629

R-squared	0.41	0.35	0.43	0.44	0.44	0.49

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. OLS estimation

Table 66: Electricity usage in kWh (ln)

	Full sample	Young urban	Young rural	Mid-age urban	Mid-age rural	Senior
Energy literacy	-0.00	0.01	0.02	-0.02	0.02	-0.01
	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Injunctive norms	-0.00	-0.02	-0.02	-0.03	0.04	0.02
	(0.02)	(0.05)	(0.05)	(0.03)	(0.03)	(0.04)
Descriptive norms	-0.01	0.00	0.04	-0.02	0.01	-0.05
	(0.02)	(0.05)	(0.05)	(0.03)	(0.03)	(0.04)
Age (household)	0.01***	0.01	0.03**	0.00	0.01	-0.00
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Household size	0.01	0.05	0.05	0.04	0.05	-0.00
	(0.03)	(0.09)	(0.06)	(0.05)	(0.03)	(0.05)
Education in years	0.02**	0.03	0.03	0.01	0.01	0.02
	(0.01)	(0.03)	(0.03)	(0.02)	(0.01)	(0.02)
Income 3'000-4'459	0.24***	0.33	0.61	0.17	-0.08	0.20
	(0.09)	(0.37)	(0.38)	(0.19)	(0.15)	(0.12)
Income 4'500-5'999	0.16*	0.40	0.41	0.17	-0.23*	0.01
	(0.09)	(0.34)	(0.35)	(0.19)	(0.14)	(0.13)
Income 6'000-8'999	0.12	0.34	0.27	0.07	-0.23*	0.06
	(0.08)	(0.36)	(0.32)	(0.19)	(0.12)	(0.12)
Income 9'000-12'000	0.14	0.40	0.13	0.16	-0.22*	-0.02
	(0.09)	(0.35)	(0.35)	(0.19)	(0.13)	(0.13)
Income 12'000 or more	0.18*	0.54	0.50	0.15	-0.29*	0.13
	(0.09)	(0.35)	(0.34)	(0.19)	(0.16)	(0.20)
Couple without children	0.22***	0.02	0.18	0.18*	0.28***	0.18*
	(0.05)	(0.18)	(0.17)	(0.10)	(0.09)	(0.09)
Couple with children	0.39***	-0.01	0.17	0.29*	0.43***	0.34*
	(0.09)	(0.31)	(0.22)	(0.16)	(0.14)	(0.18)
Single parent with one or more children	0.05	-0.13	-0.94**	0.09	0.11	0.04
	(0.08)	(0.71)	(0.40)	(0.15)	(0.15)	(0.20)
Patchwork family	0.35***	-0.37	0.25	0.48***	0.35**	-1.06***
	(0.10)	(0.58)	(0.34)	(0.16)	(0.14)	(0.19)
Non-family shared household	0.08	-0.24	-0.29	0.30**	0.22	0.12
	(0.11)	(0.41)	(0.39)	(0.14)	(0.23)	(0.16)
Swiss	0.02	0.09	-0.13	0.04	0.08	0.13
	(0.05)	(0.14)	(0.13)	(0.09)	(0.09)	(0.18)
Agglomeration	0.06*					0.07
	(0.04)					(0.07)
Countryside	0.10**		-0.10		0.06	0.15*
	(0.05)		(0.11)		(0.06)	(0.08)
Female	-0.05*	0.04	-0.07	-0.07	-0.07	-0.04
	(0.03)	(0.10)	(0.11)	(0.07)	(0.06)	(0.06)
Owner	0.11***	0.31	0.31**	0.01	0.03	0.16**
	(0.04)	(0.22)	(0.14)	(0.08)	(0.08)	(0.07)
Accommodation 2000-2009	0.13**	0.09	0.13	0.05	0.16*	0.13
	(0.06)	(0.21)	(0.18)	(0.11)	(0.08)	(0.17)
Accommodation 1990-1999	0.12*	0.46*	0.16	-0.03	0.26***	-0.10
	(0.06)	(0.26)	(0.19)	(0.13)	(0.09)	(0.16)
Accommodation 1980-1989	0.23***	0.34	0.31*	0.12	0.16	0.25*

	(0.07)	(0.26)	(0.17)	(0.12)	(0.13)	(0.15)
Accommodation 1970-1979	0.14**	0.28	0.22	0.06	0.13	0.03
	(0.06)	(0.20)	(0.19)	(0.14)	(0.11)	(0.15)
Accommodation 1960-1969	0.14**	0.08	0.13	0.04	0.28**	0.09
	(0.06)	(0.22)	(0.19)	(0.13)	(0.12)	(0.15)
Accommodation before 1960	0.15***	0.29	0.22	-0.02	0.17*	0.09
	(0.06)	(0.22)	(0.17)	(0.11)	(0.10)	(0.16)
Accommodation do not know	0.18	0.43*	-0.49	-0.30	0.51***	0.09
	(0.15)	(0.25)	(0.61)	(0.24)	(0.18)	(0.26)
Accommodation size (ln)	0.42***	0.54**	0.59***	0.46***	0.32***	0.40***
	(0.06)	(0.22)	(0.17)	(0.12)	(0.10)	(0.11)
Number of rooms	0.05**	0.15**	-0.02	0.01	0.03	0.03
	(0.02)	(0.06)	(0.07)	(0.04)	(0.04)	(0.05)
Number of bathrooms	0.04	-0.10	-0.02	0.11**	0.09**	0.00
	(0.03)	(0.12)	(0.10)	(0.05)	(0.04)	(0.06)
Number of other/garages	0.02	0.02	0.05	0.02	-0.00	0.03
	(0.01)	(0.05)	(0.07)	(0.04)	(0.02)	(0.03)
Flat in a building with less than 5 flats	-0.24***	-0.12	0.05	-0.39***	-0.23**	-0.33***
	(0.05)	(0.18)	(0.16)	(0.13)	(0.11)	(0.09)
Flat in a building with 5 to 10 flats	-0.39***	-0.23	-0.09	-0.41***	-0.52***	-0.47***
	(0.05)	(0.14)	(0.15)	(0.09)	(0.12)	(0.08)
Flat in a building with more than 10 flats	-0.37***	-0.02	-0.11	-0.39***	-0.51***	-0.46***
	(0.05)	(0.17)	(0.20)	(0.09)	(0.10)	(0.09)
Solar-thermal yes	-0.12**	0.03	-0.05	-0.02	-0.19***	-0.20**
	(0.05)	(0.19)	(0.27)	(0.10)	(0.07)	(0.10)
Photovoltaic yes	-0.04	-0.16	0.06	0.03	0.03	-0.25*
	(0.06)	(0.16)	(0.24)	(0.14)	(0.07)	(0.14)
Electricity warm water yes	0.22***	0.23	0.23*	0.32***	0.18**	0.23***
	(0.04)	(0.15)	(0.13)	(0.08)	(0.09)	(0.07)
Electricity heating yes	0.28***	-0.01	0.12	0.21**	0.32***	0.49***
	(0.05)	(0.20)	(0.16)	(0.10)	(0.09)	(0.10)
Minergie yes	-0.03	0.09	-0.32*	-0.25***	0.20***	0.04
	(0.05)	(0.18)	(0.17)	(0.09)	(0.08)	(0.09)
Minergie do not know	0.04	0.17	0.03	-0.05	0.01	0.06
	(0.05)	(0.16)	(0.17)	(0.09)	(0.10)	(0.09)
Electricity price (ln)	-0.00	-0.07	-0.04	0.05	-0.02	-0.02
	(0.02)	(0.07)	(0.08)	(0.03)	(0.06)	(0.04)
Constant	4.77***	3.38***	3.02***	5.12***	5.55***	5.69***
	(0.31)	(1.19)	(1.00)	(0.60)	(0.52)	(0.71)
Canton controls	Yes	Yes	Yes	Yes	Yes	Yes
Year controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2606	371	316	564	791	562
R-squared	0.46	0.37	0.47	0.48	0.46	0.58

Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. OLS estimation