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Swiss Household Energy Demand Survey: Past experiences and new perspectives

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Abstract

This paper is intended as a reference document for the users of the Swiss Household Energy Demand Survey (SHEDS). We outline the survey's objectives, provide a description of its structure and design, and showcase a selection of potential applications. SHEDS has been fielded annually between 2016 and 2021. Since 2021, the survey is planned every second year until 2029, resulting in a total of ten waves over a fourteen-year period. While presenting a brief history of SHEDS and its utilization in the past, we discuss new perspectives of data requirements for energy research in Switzerland. We also provide some pathways for achieving a wider usage by the energy-research community in particular energy-system modelers.

*The subject of this paper is a household survey, developed by a collaborative effort of many researchers. The design has been coordinated by these authors accompanied by Iljana Schubert and Paul Burger. Sylvain Weber conducts the survey's coding and online implementation. The data set has grown to its actual form thanks to about 13,000 respondents who have thus far completed the survey, in particular to a number of them who provided us with helpful comments and criticisms. The respondents are sampled by Intervista, a Swiss marketing research company, whose outstanding collaboration and advisement helped us in our journey. We acknowledge the financial support of Innosuisse Grant KTI. 1155000154, and the Swiss Federal Office of Energy's SWEET programme. This paper is part of the activities of SWEET CoSi (SWiss Energy research for the Energy Transition: Co-Evolution and Coordinated Simulation of the Swiss Energy System and Swiss Society). We thank Dylan Oliveira for his excellent assistance in preparing the tables and figures.

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1 Introduction

The Swiss Household Energy Demand Survey (SHEDS)[1] is a data initiative stemming from a multidisciplinary collaboration among researchers under the umbrella of the Competence Center for Research in Energy, Society, and Transition (SCCER CREST) between 2015 and 2020. With the termination of SCCER CREST in March 2021, and the advent of the Swiss Federal Office for Energy's SWEET program, SHEDS has found a new host in the SWEET CoSi research consortium[2] as of January 2023. The SHEDS data currently includes seven waves with information from about 13,000 respondents that are sampled from the Intervista Online Access Panel.[3]

The SWEET CoSi research program is a multidisciplinary collaboration rooted in engineering, economics, social sciences and humanities. As its title suggests CoSi (Co-Evolution and Coordinated Simulation of the Swiss Energy System and Swiss Society) focuses on the interactions between society and the energy system.

As a part of SCCER CREST's work package 2 ("Change of Behavior"), SHEDS has provided an empirical basis for addressing various research questions about household energy demand and related consumption and investments. Thus far, most of the analyses aimed at characterizing households' behaviors and their change. On the other hand, the SWEET CoSi's research program focuses on energy systems and their pathways to a sustainable future. While being interested in households behavior, the emphasis is on their

[1]SHEDS is open access. More details including codebooks and technical documents are available at: sweet-cross.ch/sheds.

[2]More information available at: www.sweet-cosi.ch.

[3]More information available at: www.intervista.ch/intervista-online-panel.

integration into energy system models. In this context, SHEDS aims to go beyond serving micro-econometric models of behavior and preferences into developing a collaboration basis for integrating individual-level data into energy models as well as related scenarios and narratives. This ambition brings about a new perspective for SHEDS, but raises a number of questions about the survey design.

This paper's objective is twofold. First, we would like to provide a descriptive analysis of the collected data set and its evolving structure. This analysis extends upon our initial description reported by Weber et al. (2017), covering all waves available to date (2016, 2017, 2018, 2019, 2020, 2021, and 2023). The current paper can therefore be cited as a reference for all SHEDS users.[4] Secondly, We aim to provide a critical discussion of SHEDS' new perspectives while providing a brief presentation of our experience during the last decade. This paper is therefore an attempt to identify relevant questions and suggestions for an adaptive survey design that can facilitate a better integration of data in energy system models.

2 Objectives

Weber et al. (2017) provides a description of SHEDS' objectives and added values as compared to other available survey data in Switzerland. The two main objectives can be summarized as providing empirical bases for 1) understanding household behavior and its change, and 2) evaluating the effec-

[4] Suggested citation: Farsi, M. and S. Weber (2024). Swiss Household Energy Demand Survey: Past experiences and new perspectives. IRENE working paper 24-06, Institute of Economic Research.

tiveness of new policy measures and business models for changing individual behaviors. To achieve these objectives in an efficient manner, we aimed at a large-scale sample that could accommodate a number of discrete choice experiments. The outcome was a rolling panel data set with about 5,000 observations per year and a modular structure that facilitates added 3 to 5 choice experiments per wave on subsamples of returning respondents.

SHEDS was developed on the basis of six fundamental axes:

1. Need for longitudinal data allowing an unbiased estimation of behavioral changes using panel data models;

2. Inclusion of multiple energy domains in order to provide information about relationship between various behavioral indicators within a given household or individual;

3. Inclusion of multiple disciplines in the specification of various dependent variables and explanatory factors;

4. Flexibility of design to accommodate new questions and experimental modules, while adapting to ongoing research needs and current policy questions;

5. Prioritizing policy questions readily applicable to energy transition over fundamental research;

6. Maintaining an optimal length given the relatively available budget, while responding to all data requirements from various researchers within the consortium.

Appendix 1 provides a list of publications that have used SHEDS. Examining this list can help us assess the extent of our achievements regarding these objectives. Observing a relatively large number of discrete choice experiments or survey experiments (total of 23) embedded in SHEDS and the resulting 16 peer-reviewed publications, we can conclude that SHEDS has been successful in providing the research community with a data platform for evaluating the effects of policy measures and business models. Meanwhile, there are a number of studies that analyzed the actual behavior (total of 20). However, we can observe that little has been done with observed longitudinal changes via panel data. There are only two exceptions (Tilov, Farsi, et al. 2020; Tilov and Weber 2023), each focusing on a four-year interval. This can be partly explained by the relatively short time-dimension of the panel, a limitation that is now mitigated with 7 waves (over 8 years). We contend however that associating longitudinal changes to detectable causal factors is an important empirical challenge that is often less rewarding in terms of publication.

3 Survey design and structure

SHEDS is designed by a collaborative team of researchers from various disciplines such as psychology, sociology, marketing, and economics. This collaboration has led to a framework paper (Burger, Bezençon, et al. 2015) that was used to guide the survey design with a common agenda focusing on energy-demand behaviors among Swiss households.

The survey is organized in a modular structure with several core modules that are repeated in every wave. The core modules include questions about energy-demand behavior and related equipment in three domains: electricity, heating and mobility. Three additional modules deal with socioeconomic characteristics, psychological variables and social norms. In each wave, the new respondents (who participate for the first time) are presented with the entire questionnaire. However, some of the questions pertaining to variables deemed to be time-invariant[5] are excluded for the returning respondents (who have completed the survey in at least one previous wave). In addition, questions related to some psychological and lifestyle variables are collected only once for each new respondent. In each wave a subsample of returning respondents are asked to participate in one of the embedded choice experiments (CE) in a separate dedicated module.

The questionnaire is prepared in three languages (German, French and English) and are implemented in the online Qualtrics platform.[6] An internal test among half a dozen of respondents among our research teams is used to correct eventual errors for new questions. In each wave, we conduct a pretest survey with around 50 respondents that are invited to complete the entire survey (including the CE module). The pretest survey gives respondents the opportunity to provide comments and ask questions. These comments are used to fine-tune the survey before inviting the main pool of respondents.

The survey was initially planned for five years from 2016 to 2020. Available funds allowed us to conduct an additional wave at a smaller scale in

[5]These are the variables that are not likely to change in a yearly basis.
[6]Available at: www.qualtrics.com.

2021. As a part of new consortium SWEET CoSi, four additional waves are proposed from 2023 to 2029 on a bi-annual basis. The survey length is about 20 to 30 minutes. In general, the survey is fielded between April and June. The sampling procedure focuses on individuals who are at least partly involved in the management of their household's expenditure. This is identified by a short question at the beginning of the survey. We prioritize respondents who have participated in a previous wave. New respondents are invited in a second stage, depending on the achieved sample size among returning respondents. It normally takes about five weeks to reach the planned sample size of about 5,000 respondents.[7]

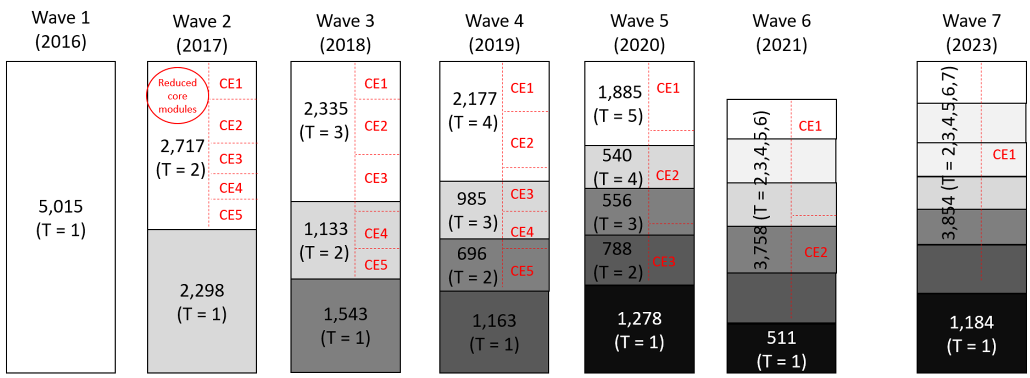
The final sample satisfies a series of preset quotas designed to mimic the Swiss population with respect to age (18-34: 30%, 35-54: 40%, 55+: 30%), gender (female: 51%, male: 49%), language region (German: 75%, French: 25%, the Italian-speaking canton Ticino is excluded) and home ownership (homeowner: 37.5%, tenant: 62.5%). While the entire sample can be considered as a representative sample based on these variables, the number of missing values could vary significantly across variables and across sub-populations. Therefore, depending on the analysis and the variables of interest, it is possible that the resulting sample loses its representative structure.

Figure 1 shows the SHEDS waves and the embedded choice experiments (CE). The figure also shows the rolling panel's structure by including the number of respondents by the number of periods (T) with previous records.

[7] Data for the first wave in 2016 was collected in only 2 weeks during. Since the second wave, data collection is slower because only returning respondents are contacted at the beginning and fresh respondents are contacted afterwards to fill the sample.

In each wave, the new respondents are denoted by $T = 1$, whereas the returning respondents have $T > 1$. Overall, it is more likely to have returning respondents with newer waves thus improving the panel's longitudinal aspect.

Figure 1: Data collected in waves 2016-2023



3.1 Attrition analysis

In order to understand the attrition across waves, we provide a descriptive analysis of the number of respondents and their return rates. This analysis helps us not only to understand the dataset's potential for identifying longitudinal changes, but provides a basis for setting the interval between consecutive waves (currently planned as 2 years). Table 1 lists the number of new and returning respondents by wave. We observe that the share of returning respondents grows constantly at the outset but stays more or less constant around three quarters. The exception in 2021 is related to the smaller sample size in that wave.

The matrix in Table 2 presents the return rate from the years indicated in the rows to the years indicated in the columns. The numbers in the diagonal

Table 1: Number of new and returning respondents by wave

	2016	2017	2018	2019	2020	2021	2023
All respondents	5015	5015	5011	5021	5047	4269	5038
New respondents	5015	2298	1543	1163	1278	511	1184
Returning respondents	0	2717	3468	3858	3769	3758	3854
Returning share	0%	54%	69%	77%	75%	88%	76%

show that almost 60% of the respondents in any given wave also answer the next wave. Said otherwise, attrition is about 40-45% between any two waves. As tenure in the survey increases, attrition naturally grows but seems to stabilize around 70% after 5 years: more than 30% of the respondents who entered in the survey in 2016 (first line of the matrix) also answered the 2021 and/or the 2023 waves. Interestingly, the pool of respondents who answered in 2021 (last line of the matrix) show a lower attrition rate at about 38% in 2023, despite the fact there was a 2-year interval between these waves. However, this exception is partly explained by the smaller sample size in 2021 and the associated larger proportion of returning respondents.

Tables 3 shows the return rates separately for each entry cohort (each row indicates the entry year of a cohort). By design, the first line is identical to that in Table 2 and is the only one based on the full sample. The subsequent

Table 2: Return rates, from row to column years

	2017	2018	2019	2020	2021	2023
2016	54%	47%	43%	38%	31%	32%
2017	-	58%	52%	44%	37%	38%
2018		-	59%	50%	43%	41%
2019			-	58%	50%	47%
2020				-	58%	53%
2021					-	62%

Reading example: among all respondents to wave 2018, 59% answered wave 2019 and 50% answered wave 2020.

rows are based on fewer observations, since new respondents were then only integrated in the panel to reach a total of 5,000 respondents. We observe that the return rate is slightly decreasing cohort after cohort, but it generally remains above 30% for all cohorts and all years.

Table 4 focuses on returning respondents that is, respondents who have participated in at least one previous wave. This matrix suggests that the return rate is more or less stable around two thirds for returning respondents. Clearly, individuals who repeat the survey are relatively more likely to come back again.

Finally, in order to assess the extent to which we can rely on continuity hence tending to a balanced panel, we produce a matrix in Table 5 that shows the proportion of respondents who participated in several consecutive waves without interruption (from the row year until the column year). Here again, we observe more or less stable return rates, suggesting about 40% continuous participation for 3 waves (from year T to year $T+2$), and about 28% for 4 waves (between year T and year $T+3$). We can also observe that continuity for 5 waves is about 20%. Given the relatively large number of

Table 3: Return rates by entry cohort, from row to column years

	2017	2018	2019	2020	2021	2023
2016	54%	47%	43%	38%	31%	32%
2017	-	49%	43%	34%	29%	30%
2018		-	45%	36%	32%	29%
2019			-	46%	36%	33%
2020				-	47%	41%
2021					-	44%

Reading example: among respondents who first appeared in wave 2018, 45% answered wave 2019 and 36% answered wave 2020.

Table 4: Returning respondents' return rates, from row to column years

	2017	2018	2019	2020	2021	2023
2017	-	66%	60%	52%	44%	44%
2018		-	66%	56%	47%	47%
2019			-	62%	54%	51%
2020				-	62%	57%
2021					-	65%

Reading example: among respondents who first appeared in wave 2016 or 2017 and answered wave 2018, 66% answered wave 2019 and 56% answered wave 2020.

respondents (5,000 per wave) this rate amounts to about 1,000 respondents with data for 5 continuous waves. This provides a reasonably large sample for investigating longitudinal changes based on a balanced panel. However, as we see later, depending on the variable of interest, the number of missing values could affect the effective sample size.

Table 5: Return rates, from row to column years without interruption

	2017	2018	2019	2020	2021	2023
2016	54%	36%	26%	20%	14%	11%
2017	-	58%	40%	29%	21%	16%
2018		-	59%	40%	28%	21%
2019			-	58%	39%	28%

Reading example: among all respondents to wave 2018, 40% answered waves 2019-2020 and 28% answered waves 2019-2021.

4 A descriptive analysis

In this section, we provide a descriptive analysis of a selection of variables to illustrate the dataset's potential. Our focus is on households' energy demand and their investments in equipment and appliances. We also consider an energy-behavior indicator as well as a segmentation application that could be used to estimate households' electricity saving potential.

4.1 Energy demand

The following analysis focuses on energy consumption in three domains: electricity, heating, and mobility. We use both expenditures (in CHF) and physical measures (electricity in kWh or distance in km) when available. An exploratory analysis prompts us to detect a number of outlier values. We therefore exclude all values outside an interval of 1.5 times the interquartile range, considering these as outliers that could be erroneous observations. In addition, values smaller than or equal to one are excluded to accommodate logarithmic transformations that we use in the regressions.

Table 6 shows the summary statistics for energy consumption variables in the three selected domains. The number of valid observations and respondents is above 23,000 and 9,000 for expenditure variables and about 14,000 and 6,000 for physical measures. Table 6 also lists the number of respondents with valid information in T periods, for $T = 1$ to 7. Only a small minority of respondents have valid data for 5 periods or more. Yet, a majority of respondents have data for at least two periods, hence usable for a longitudinal analysis with individual fixed effects. This share will certainly increase as the panel extends to cover more waves.

It is also important to note that all demand indicators in the Table 6 refer to the year (12-month period) prior to the individual response date, with the exception of mobility expenditure that is referred to the month preceding the survey (fielded between April and June).

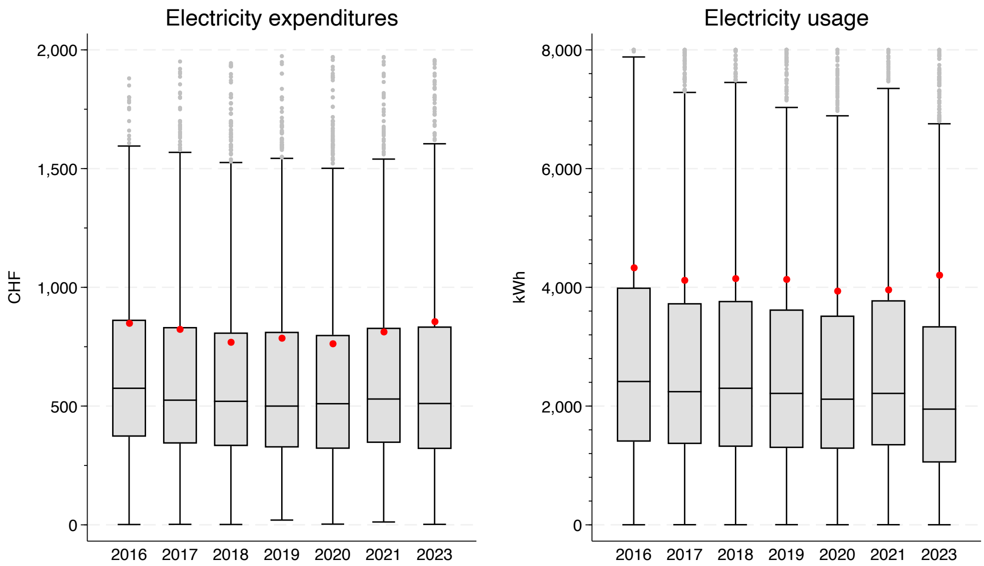
Figure 2 uses box plots to illustrate the evolution of electricity demand over the observation period. Similarly Figure 3 depicts the evolution of demand for heating and mobility.

Our first observation is on the large variability in each wave, which can partly be explained by observable determinants. However, as we will see later, our regression analysis suggests substantial unobserved heterogeneity among households. This between-household variability can be captured by individual fixed effects. This highlights the importance of meaningful longitudinal dimension in the data.

Table 6: Description of energy-demand variables

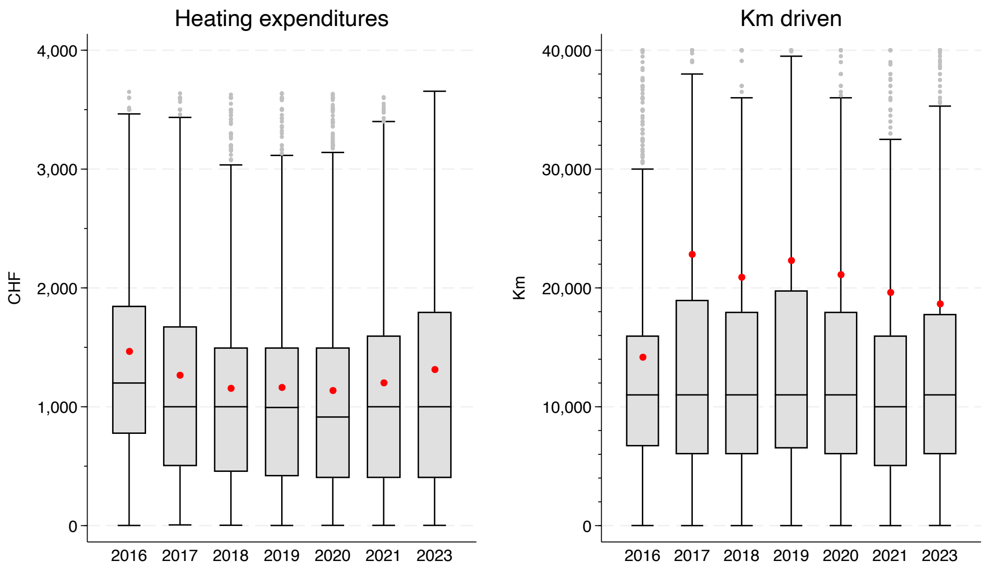
Variable	Electricity expenditures	Electricity usage	Heating expenditures	Mobility expenditures	Km driven
Mean	638.8	2872.6	1235.1	118.5	12663.8
SD	416.4	2122.6	849.2	71.1	8572.3
Min	1.4	1.1	1.2	2.0	2.0
Median	530.0	2294.0	1082.0	100.0	11000.0
Max	1975.2	9624.0	3850.0	345.0	40250.0
Observations	23847	14213	23987	23376	14177
Respondents	9874	6302	10170	9312	5986
Measurement	Electricity expenditures in CHF over the last year	Electricity usage in kWh over the last year	Heating expenditures in CHF over the last year	Fuel expenditures in CHF over the last month	Kilometers driven over the last year
Respondents with valid data in T periods:					
T=1	4194	3007	4347	3822	2504
T=2	2049	1272	2176	1844	1355
T=3	1384	775	1447	1315	859
T=4	847	467	885	821	505
T=5	653	366	678	694	397
T=6	479	266	442	545	181
T=7	268	149	195	271	185

Figure 2: Evolution of electricity expenditures and usage



Note: Red dots represent mean values.

Figure 3: Evolution of heating expenditures and Km driven



Note: Red dots represent mean values.

Table 7 displays the results of OLS regression explaining the five variables described in Table 6 by the same selection of control variables. Several relevant observations emerge from these regressions. First, the model fit statistics point to substantial unobserved heterogeneity especially in mobility behavior (R-squared of 4% and 9%, respectively for distance driven and mobility expenditures). We also observe a relatively lower model fit for physical measures as opposed to expenditures, which could be partly related to smaller sample size and to better knowledge of expenditures by respondents, in particular in the electricity domain where consumption is not easily available. The OLS regressions can also be used to infer about various determinants of energy demand. Some of these determinants have been analyzed in previous studies using SHEDS data (e.g., Schubert, Weber, et al. 2022; Tilov, Farsi, et al. 2020; Tilov and Weber 2023).

At the risk of repeating ourselves, we highlight a few stylized facts about the variation of energy demand among Swiss households: income is an important determinant although with an inelastic relationship; there are significant economies of scale with respect to the household size; residence in urban and suburban areas is associated with lower energy demand on average; energy demand is likely to be different across linguistic border between French and German-speaking regions. We would also note that the trends cannot be measured in an OLS regressions. It is likely that the year dummies capture sample mix differences, and should be treated as incidental parameters rather than time trends.

In order to study time trends, we show the results of fixed-effect models in Table 8. These estimates are based on within-household variations, thus rep-

Table 7: OLS regressions

Variables	Electricity expenditures	Electricity usage	Heating expenditures	Mobility expenditures	Km driven
HH income (log)	0.0506*	0.142**	0.154***	0.137***	0.171***
	(0.0225)	(0.0466)	(0.0286)	(0.0239)	(0.0431)
French speaking	-0.0632**	-0.160***	0.105***	0.131***	0.0835**
	(0.0214)	(0.0391)	(0.0216)	(0.0177)	(0.0320)
Respondent's gender (1 if female)	-0.0340*	-0.0208	-0.00839	-0.0759***	-0.123***
	(0.0147)	(0.0312)	(0.0191)	(0.0159)	(0.0297)
Respondent's age					
Under 30	ref.	ref.	ref.	ref.	ref.
30 to 54	0.129***	0.373***	0.267***	-0.0303	-0.0521
	(0.0231)	(0.0683)	(0.0324)	(0.0213)	(0.0479)
55 to 65	0.216***	0.492***	0.400***	-0.127***	-0.122*
	(0.0283)	(0.0758)	(0.0381)	(0.0282)	(0.0613)
over 65	0.223***	0.484***	0.510***	-0.256***	-0.268***
	(0.0304)	(0.0751)	(0.0403)	(0.0338)	(0.0613)
Respondent's education					
Primary	ref.	ref.	ref.	ref.	ref.
Secondary	0.176**	0.254*	0.192**	0.0535	0.0589
	(0.0629)	(0.124)	(0.0726)	(0.0513)	(0.143)
University	0.151*	0.291*	0.208**	-0.00491	0.0536
	(0.0634)	(0.123)	(0.0719)	(0.0514)	(0.145)
Household size categories					
Single	ref.	ref.	ref.	ref.	ref.
2 person HH	0.227***	0.299***	0.0651*	0.0303	-0.0304
	(0.0217)	(0.0438)	(0.0278)	(0.0238)	(0.0407)
3+ person HH	0.385***	0.450***	0.112***	0.0917***	-0.0303
	(0.0260)	(0.0503)	(0.0303)	(0.0259)	(0.0434)
City	ref.	ref.	ref.	ref.	ref.
Agglomeration	0.0794***	0.152***	0.0429	0.114***	0.0914**
	(0.0220)	(0.0370)	(0.0239)	(0.0201)	(0.0344)
Countryside	0.187***	0.225***	0.0211	0.223***	0.225***
	(0.0230)	(0.0406)	(0.0250)	(0.0207)	(0.0365)
Home owner	0.0508***	0.0461	0.0470**	-0.0801***	-0.0387
	(0.0126)	(0.0269)	(0.0156)	(0.0145)	(0.0278)
House (0 if flat)	0.211***	0.199**	-0.0848*	0.141***	0.0154
	(0.0281)	(0.0638)	(0.0369)	(0.0303)	(0.0415)
Age of house (log)	0.0345***	0.0378**	0.133***	-0.0169**	-0.0149
	(0.00713)	(0.0130)	(0.00869)	(0.00600)	(0.0121)
Size of dwelling in m^2 (log)	0.412***	0.473***	0.433***	0.0544*	0.00551
	(0.0263)	(0.0495)	(0.0300)	(0.0214)	(0.0408)
Year dummies					
Year 2016	ref.	ref.	ref.	ref.	ref.
Year 2017	-0.0131	0.0787	-0.0301	0.169***	0.0872
	(0.0257)	(0.0491)	(0.0344)	(0.0266)	(0.0849)
Year 2018	-0.0554*	0.0205	-0.176***	0.159***	-0.00406
	(0.0276)	(0.0480)	(0.0377)	(0.0254)	(0.0907)
Year 2019	-0.0470	-0.0200	-0.191***	0.181***	0.0610
	(0.0301)	(0.0603)	(0.0446)	(0.0324)	(0.0900)
Year 2020	-0.0488	0.0508	-0.231***	0.0662*	0.0747
	(0.0283)	(0.0514)	(0.0453)	(0.0294)	(0.0968)
Year 2021	-0.00148	0.0169	-0.166***	-0.0117	-0.134***
	(0.0205)	(0.0437)	(0.0313)	(0.0240)	(0.0353)
Year 2023	-0.0790**	-0.294***	-0.186***	0.144***	0.196***
	(0.0258)	(0.0518)	(0.0366)	(0.0256)	(0.0540)
Constant	3.209***	3.038***	2.507***	3.004***	7.655***
	(0.199)	(0.424)	(0.259)	(0.211)	(0.409)
Observations	9363	5401	8974	9415	4922
Number of households	1651	1325	1670	1755	1413
Adjusted R-squared	0.239	0.190	0.158	0.0893	0.0395

Robust standard errors clustered at the level of the ZIP code in parentheses.
Dependent variables are in logarithms.
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

resenting longitudinal changes. Here again, relatively low model-fit estimates point to a strong heterogeneity even after controlling for household fixed effects. The regressions detect a reduction in the 2019-2021 period, probably related to Covid-19 crisis, and a recovery in 2022-2023.[8] It is interesting to note that the number of respondents in this analysis remain reasonably high allowing a meaningful analysis of longitudinal changes. This is directly related to the relatively high return rate among respondents.

We contend that longitudinal analyses (such as those in Table 8) are primordial for monitoring the micro-level energy-demand changes especially in today's context where energy policies are expected to gradually reduce energy consumption. Unfortunately, our data do not detect any persistent reduction in energy consumption. This is a remarkable result if it is opposed to the

Table 8: Fixed-effect regressions

Variables	Electricity expenditures	Electricity usage	Heating expenditures	Mobility expenditures	Km driven
Year 2017	-0.00316	0.0365	0.0491*	0.0320*	0.0262
	(0.0145)	(0.0315)	(0.0220)	(0.0133)	(0.0282)
Year 2018	-0.0619***	0.00777	-0.0184	0.0103	-0.0228
	(0.0151)	(0.0321)	(0.0233)	(0.0139)	(0.0311)
Year 2019	-0.0509***	-0.0123	-0.0484*	-0.0173	0.0348
	(0.0152)	(0.0310)	(0.0236)	(0.0147)	(0.0311)
Year 2020	-0.0675***	-0.0293	-0.0710**	-0.0972***	-0.0436
	(0.0156)	(0.0328)	(0.0240)	(0.0150)	(0.0328)
Year 2021	-0.0174	-0.0173	-0.0204	-0.158***	-0.164***
	(0.0166)	(0.0342)	(0.0246)	(0.0160)	(0.0333)
Year 2023	-0.0390*	-0.109**	0.0669**	-0.0578***	-0.0536
	(0.0178)	(0.0360)	(0.0258)	(0.0171)	(0.0322)
Observations	23847	14213	23987	23376	14177
Number of households	9874	6302	10170	9312	5986
Within R-squared	0.00305	0.00449	0.00545	0.0202	0.00542
Overall R-squared	0.00180	0.00895	0.00132	0.00237	0.00251

Standard errors in parentheses.
Dependent variables are in logarithms.
The base year is 2016.
The regressions include household fixed effects.
* p<0.05 ** p<0.01 *** p<0.001

[8]Note that all the dependent variables (except mobility expenditure) refer to the twelve months before the survey's date in April/May.

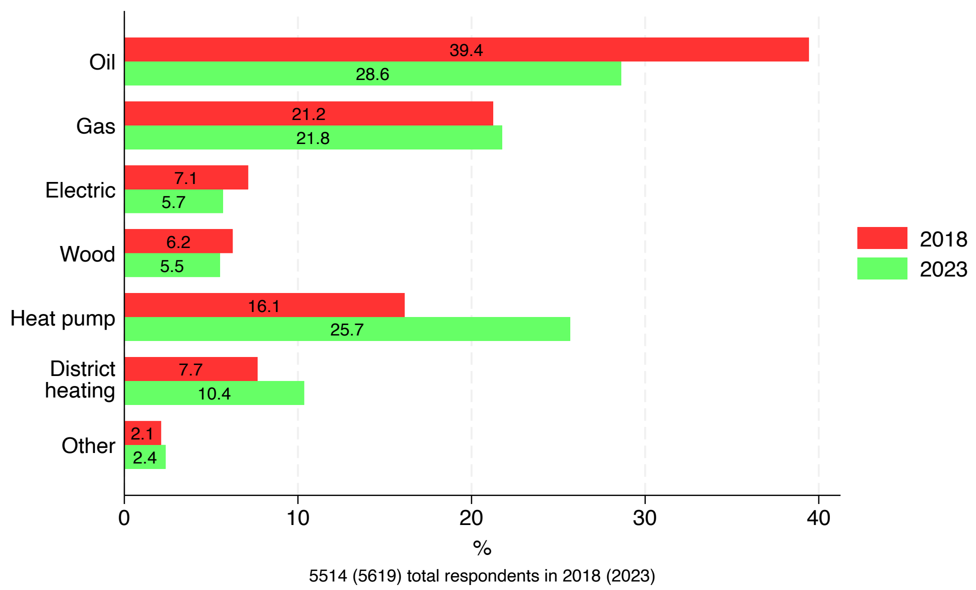
households' investment behavior (described below) suggesting a significant rise in energy efficiency.

4.2 Investments

SHEDS provides a series of energy-investment indicators at the household level. Here we focus on heating systems and car purchases between 2018 and 2023. Figure 4 shows the share of heating systems in 2018 and 2023, revealing an important substitution has occurred during the five-year interval. The share of heating oil systems has dropped by about 10 percentage points that are almost entirely picked by heat pumps.

In the mobility field, we focus on the car engine types. Figure 5 shows the distribution of engine types of the cars owned by SHEDS respondents

Figure 4: Distribution of all the Heating Systems in 2018 and 2023

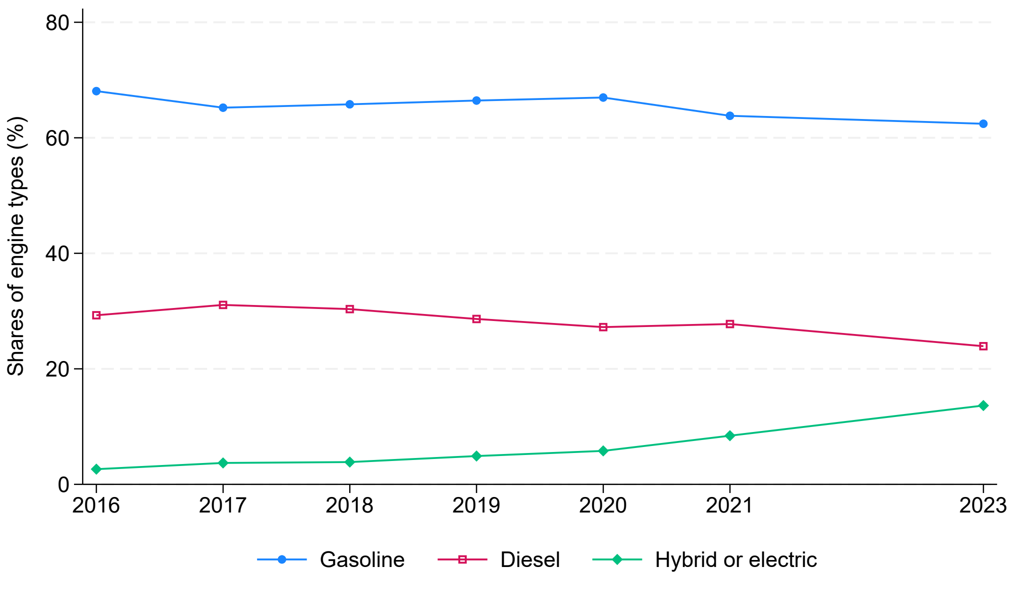


over 2016-2023.[9] A great majority of cars run on gasoline (more than 60%) or diesel (more than 20%). Yet, the share of hybrid and electric cars is increasing at a rapid pace: it multiplied by five over the observation period, from less than 3% in 2016 to almost 14% in 2023.

Among car purchased (new or second-hand), the evolution is much stronger. Figure 6 indeed shows that gasoline and diesel car purchases are declining rapidly, while the share of hybrid and electric car purchased reaches almost 40% in 2023. If the trend continues, the latter will soon be the most frequently purchased category.

We finally investigate technology switches at the time of car purchases.Figure 7 illustrates transitions from an old to a new car.[10] It clearly turns out that

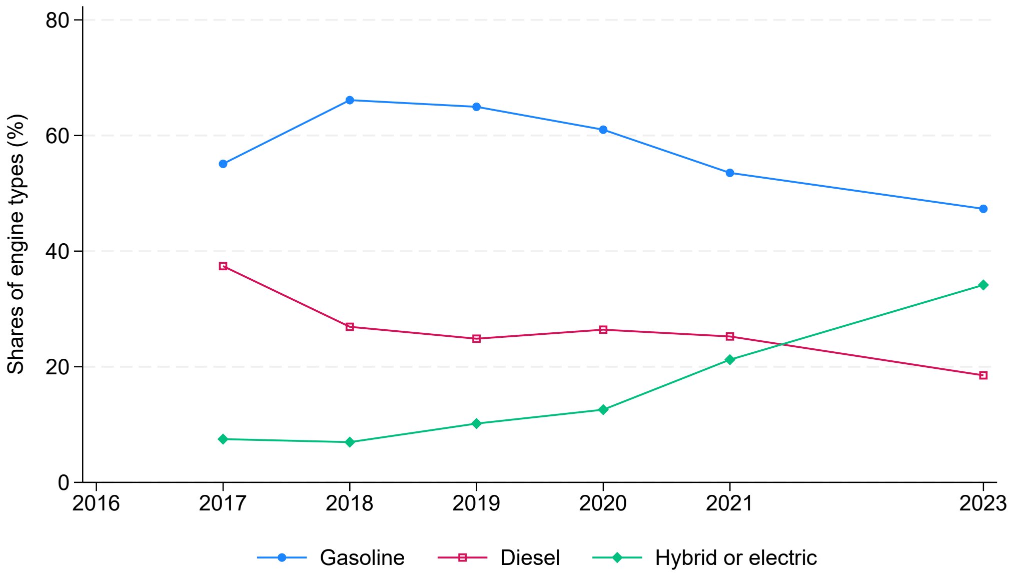
Figure 5: Distribution of engine types, all cars



[9]Around one quarter of the respondents state that they do not own a car.

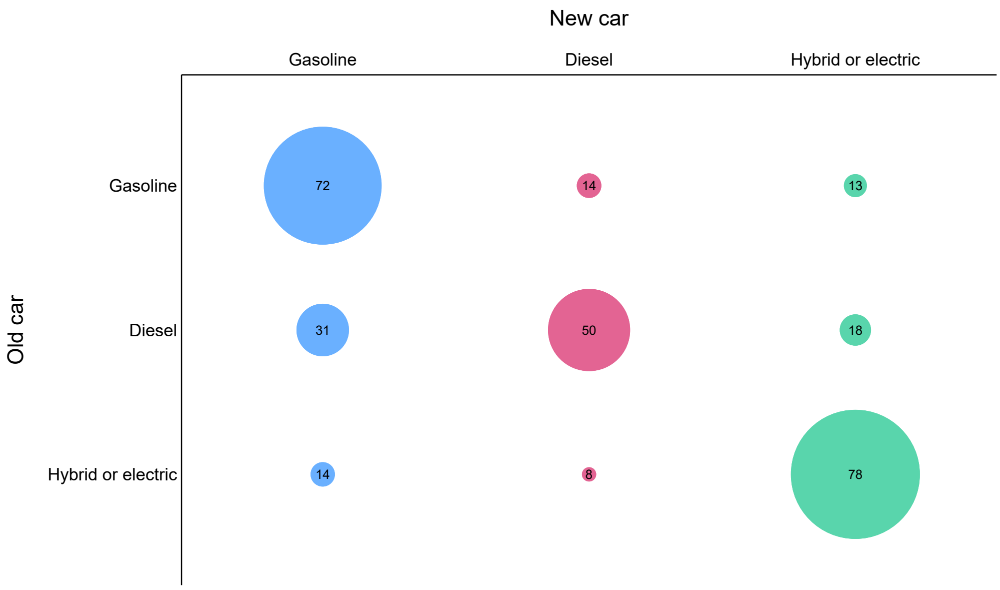
[10]Note that cars called "new" in this illustration are not necessarily new in a strict sense since they also enclose second-hand cars.

Figure 6: Distribution of engine types, purchased cars



most people stick to the same technology when they replace their main vehicle. This is also consistent with results obtained by Van Dijk, Farsi, and Weber (2021): In an experiment investigating car adoption and travel decisions, it happens that choices made in the experiment about car size and fuel type were significantly related to the real-life situations of respondents. When faced with an important decision such as purchasing a car, it appears that consumers tend to favor a technology with which they are familiar (see also Van Dijk and Farsi 2022).

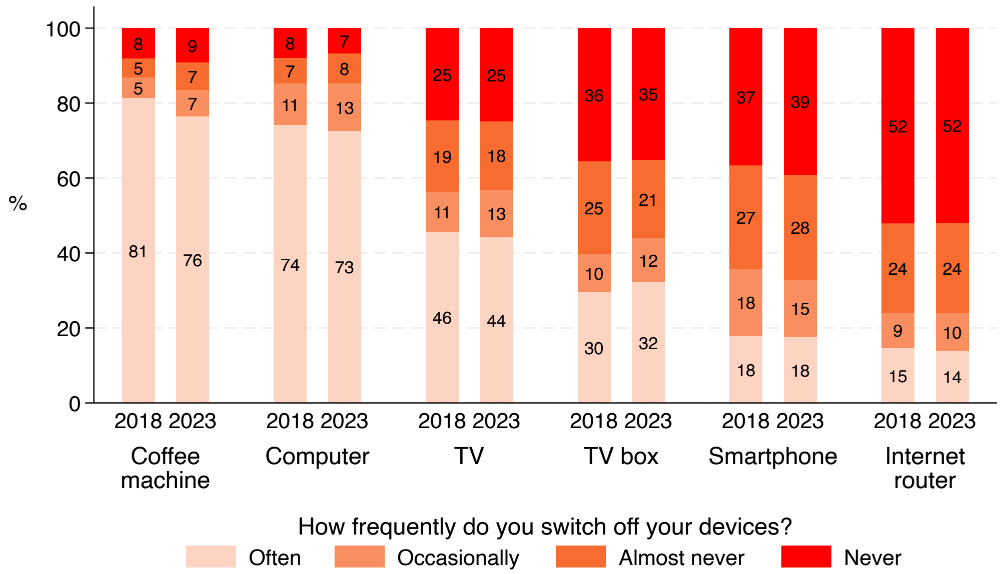
Figure 7: Transitions between engine types, 2016-2023



4.3 Behavior

A large number of behavioral indicators can be extracted from SHEDS. Here, we focus on a single behavior related to switching off a device as opposed to leaving it in standby mode. Figure 8 illustrates the comparative picture of behavior between 2018 and 2023. Overall, the data indicates no detectable evolution of conservation behavior in this particular setting but there are clear differences across devices.

Figure 8: Device switch-off as opposed to standby mode in 2018 and 2023



Note: Based on 2,400 to 4,900 observations depending on device and year.

4.4 Saving potentials via segmentation

In this section, we focus on household's yearly electricity consumption (kWh). The objective is to produce a segmentation analysis based on three electricity-demand determinants – dwelling type, household size, and heating system – in order to identify saving potentials in each segment. These determinants are selected from factors that remain largely beyond the individual's short-term control. In order to deal with implausible values (outliers), we trim all observations whose reported values lie outside an interval of 1.5 times the interquartile range. We also exclude values smaller or equal to one. We design the segmentation in a manner that the minimum segment size remains about 50 households, a size we consider as a reasonable basis for comparing consumption within each segment.

After a few iterations we settled on a classification based on four household sizes, two housing categories (houses and apartments), and three categories of heating. As shown in Table 9, this segmentation results in 24 household types with a minimum group size of 48. The table lists the 1st decile, the 1st quintile and the median value of electricity consumption for each segment.

Our ultimate objective is to provide a rough estimate of electricity-saving potential as compared to the best practice in each segment. In this analysis, we allow for some heterogeneity in exogenous variables that are unobserved to the segmentation model. Following a commonly accepted assumption in quantile analysis of productive efficiency (benchmarking), we allow for about 10 or 20 percent unobserved heterogeneity and measurement errors unrelated to best-practice behavior. With this assumption, we can consider the 1st decile or the 1st quintile as the best practice, thus providing a yardstick for measuring saving potentials.

A first look at the results in Table 9 suggests that compared to a best-practice comparable household, a majority of households can attain a substantial reduction in their electricity demand. Even looking at 1st quintiles, about 30% reduction seems to be a plausible target. Such reductions might however require a change in many factors that are not included in the analysis such as lifestyle and dwelling size. Some of these variables could be readily included in our illustrative analysis.

In order to have a better picture of saving potentials in each segment, we extend the analysis with a quantile frontier model controlling for external variables such as location indicators (city agglomeration, countryside,

Table 9: Electricity consumption indicators in 24 household segments

Household type		Number of households	Electricity consumption (kWh/year)		
			Decile	Quintile	Median
1	House, 1 person, non-electric heating	324	583	912	1758
2	House, 2 person, non-electric heating	917	1286	1805	3198
3	House, 3 person, non-electric heating	296	1313	2200	3363
4	House, >3 person, non-electric heating	620	1958	2719	4358
5	House, 1 person, electric hot water	129	700	1248	3007
6	House, 2 person, electric hot water	324	1856	2889	4810
7	House, 3 person, electric hot water	121	3252	4056	5797
8	House, >3 person, electric hot water	209	2338	3935	6029
9	House, 1 person, with heat pump	48	900	1050	4845
10	House, 2 person, with heat pump	236	2038	3295	5791
11	House, 3 person, with heat pump	112	2343	3600	5446
12	House, >3 person, with heat pump	199	2557	3360	5927
13	Apartment, 1 person, non-electric heating	1502	577	764	1203
14	Apartment, 2 person, non-electric heating	1728	934	1264	1982
15	Apartment, 3 person, non-electric heating	404	1100	1382	2283
16	Apartment, >3 person, non-electric heating	458	1146	1700	2700
17	Apartment, 1 person, electric hot water	309	720	1038	1870
18	Apartment, 2 person, electric hot water	275	1200	1767	3000
19	Apartment, 3 person, electric hot water	79	1464	1940	3890
20	Apartment, >3 person, electric hot water	86	1846	2430	3973
21	Apartment, 1 person, with heat pump	161	696	883	1284
22	Apartment, 2 person, with heat pump	257	1000	1365	2078
23	Apartment, 3 person, with heat pump	57	1048	1600	2702
24	Apartment, >3 person, with heat pump	71	1400	1855	2955

French-speaking region) and dwelling size, as well as life-style proxies such as household income and respondent's education as listed in Table 7. Since the data are pooled across several years from 2016 to 2023, we include a set of year dummies in our models. We conduct a separate regression analysis for each segment. Similar to the specification used in Table 7, we use logarithmic transformation for electricity consumption, household income and the dwelling size. In line with frontier models (in particular thick frontier models), we assume that 20% of the observations in each segment are almost perfectly efficient with a negligible saving potential. This assumption boils down to a quantile frontier estimated at the first quintile, with zero potential savings for all observations below the first quintile. For the remaining 80%, saving potential is computed as a percentage of the actual consumption based on positive regression residuals ε as follows:

$$1 - e^{-\varepsilon}$$

We explored several model specifications with different variables. The aggregate savings are not sensitive to the adopted specification. Table 10 lists the medians and means of saving potentials in each one of the 24 segments based on the model described above. The estimated savings suggest that a majority of households in each segment could achieve significant savings, with an overall average saving of 27 to 40%, depending on the household segment. Part of these reductions might however be related to factors beyond the households' control such as outdoor temperature. In other words, there is a strong within-segment heterogeneity among individual households, which could bias potential savings' estimates. In fact, the measure of our model's goodness of fit (pseudo R-squared) is quite variable, ranging from 5% to 44% depending on the given segment.

Aggregate measures of saving potential, as those listed in Table 10, could appear implausible, at least for some households. There is in fact no testable hypothesis that can disentangle a genuine saving possibility from an unobserved factor beyond the household's control. This challenge is especially important in case of strong unobserved heterogeneity. We therefore propose to focus on specific savings that are plausible in the short run. Based on the individual potential saving estimates we can compute the share of house-

Table 10: Electricity saving potential

	Household type	Saving potential (median)	Saving potential (mean)
1	House, 1 person, non-electric heating	40%	38%
2	House, 2 person, non-electric heating	40%	36%
3	House, 3 person, non-electric heating	39%	37%
4	House, >3 person, non-electric heating	36%	33%
5	House, 1 person, electric hot water	44%	40%
6	House, 2 person, electric hot water	36%	35%
7	House, 3 person, electric hot water	29%	27%
8	House, >3 person, electric hot water	35%	33%
9	House, 1 person, with heat pump	36%	40%
10	House, 2 person, with heat pump	49%	40%
11	House, 3 person, with heat pump	29%	28%
12	House, >3 person, with heat pump	42%	36%
13	Apartment, 1 person, non-electric heating	38%	35%
14	Apartment, 2 person, non-electric heating	34%	33%
15	Apartment, 3 person, non-electric heating	36%	33%
16	Apartment, >3 person, non-electric heating	36%	34%
17	Apartment, 1 person, electric hot water	45%	40%
18	Apartment, 2 person, electric hot water	43%	37%
19	Apartment, 3 person, electric hot water	46%	44%
20	Apartment, >3 person, electric hot water	42%	37%
21	Apartment, 1 person, with heat pump	35%	34%
22	Apartment, 2 person, with heat pump	33%	32%
23	Apartment, 3 person, with heat pump	35%	34%
24	Apartment, >3 person, with heat pump	38%	38%

holds that can achieve a specific percentage savings such as 10%. Table 11 summarizes the share of households in each segment that can achieve 10% or 20% reduction in their electricity consumption. According to these estimates a majority of households (more than two thirds) could achieve 10 percent savings.

Table 11: Reduction in households electricity consumption

Household type		Fraction (%) of households that can achieve 10% or 20% reduction in their electricity consumption 10%	20%
1	House, 1 person, non-electric heating	77%	71%
2	House, 2 person, non-electric heating	75%	68%
3	House, 3 person, non-electric heating	73%	67%
4	House, >3 person, non-electric heating	72%	68%
5	House, 1 person, electric hot water	72%	69%
6	House, 2 person, electric hot water	74%	66%
7	House, 3 person, electric hot water	68%	59%
8	House, >3 person, electric hot water	70%	67%
9	House, 1 person, with heat pump	60%	55%
10	House, 2 person, with heat pump	72%	68%
11	House, 3 person, with heat pump	67%	62%
12	House, >3 person, with heat pump	71%	66%
13	Apartment, 1 person, non-electric heating	74%	68%
14	Apartment, 2 person, non-electric heating	75%	67%
15	Apartment, 3 person, non-electric heating	71%	63%
16	Apartment, >3 person, non-electric heating	72%	64%
17	Apartment, 1 person, electric hot water	74%	67%
18	Apartment, 2 person, electric hot water	74%	66%
19	Apartment, 3 person, electric hot water	72%	69%
20	Apartment, >3 person, electric hot water	73%	70%
21	Apartment, 1 person, with heat pump	68%	64%
22	Apartment, 2 person, with heat pump	70%	64%
23	Apartment, 3 person, with heat pump	73%	68%
24	Apartment, >3 person, with heat pump	70%	66%

5 Discussion and perspectives

We have described the panel structure of the SHEDS data available at this stage. The results suggest that the attrition rate is sufficiently low in order to conduct meaningful longitudinal analyses. Extending the panel by re-inviting the more than 10,000 respondents who have completed the survey in at least one of the previous waves will certainly help improve the longitudinal aspect.

The future waves now planned for 3 biannual waves with about 5,000 respondents, will provide us with a ten-period panel data covering 14 years from 2016 to 2029. Given that a smaller sample size would lead to a better return rate among previous respondents, we can expect that splitting the 3 biannual waves to 6 annual waves (each with about 2,500 respondents) will substantially improve the longitudinal dimension without any increase in budget requirements.

We have also shown that the SHEDS panel data is not as representative as each cross-sectional wave, mainly due to attrition but also to the various number of missing or invalid values. It is however important to note that longer panels are likely to be less representative, thus suggesting a trade-off between building a representative panel and collecting data that are useful for longitudinal analysis. If we prioritize the longitudinal dimension, we should favor annual waves. But if we tend to value a representative sample, we should stick to the biannual panel.

SWEET CoSi's research program focuses on evolution of energy systems, thus highlighting the importance of monitoring the evolution of energy-demand behavior. Identifying behavior at the household level requires an unbiased panel data analysis with individual fixed effects. Longer panels with repeated observations from the same households hence provide a better possibility for such analyses. On the other hand, repeated cross-sectional data from fairly representative samples could be sufficient for energy system modeling. This observation combined with the fact that energy models with heterogeneous agents require a reasonable sample size in various subpopulation groups leads us to prioritize the cross-sectional sample size over longitudinal dimension.

Choice experiments and other stated-preference methods have been used as valuable assessment tools for a variety of policy measures and business models. Such experimental data can be extremely helpful for identifying behavioral trends and responses in emerging markets and other contexts where revealed-preference data are not readily available. Moreover, stated-preference data can provide insights on voting behavior and acceptance of energy-related policies. Another question is whether we can assess the future inclusion of Canton Ticino, the Italian-speaking canton with about 4% of Swiss population. Again, if we favor the longitudinal dimension, new respondents from Ticino would not provide an added value, especially if we consider 3 biannual waves. However, including about 200 respondents from Ticino for each one of the three waves may be helpful towards a marginally better representation of the Swiss population.

We have shown through a series of simple applications how the data can be used in various analyses. Focusing on a selection of energy-demand indicators, these examples illustrate a range of possible applications for energy modeling and systemic analysis. We identify two types of applications: First, the econometric analysis of demand indicators and their temporal changes allows to estimate various determinants of household energy demand. The estimated gradients and elasticities with respect to these determinants such as household's income and size, ownership and the building's age can be used in energy demand predictions. Second, segmentation analysis can be readily applied to demand determinants in order to identify various household clusters with comparable behaviors and/or attitudes.

Overall, these examples point to a variety of applications that could guide energy analysts to refine their models based on realistic behavioral assumptions. Last no least, we hope that this work could contribute in moving the SHEDS initiative beyond a mere data service to a dynamic and adaptive survey design with systematic and continuous exchange between energy researchers from various disciplines.

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Appendix: Publications based on SHEDS[11]

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[11] Publications based on experiments are labeled by an asterisk (*).

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