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Estimating residential electricity demand: New empirical evidence

Nina Boogen [a,c], Souvik Datta [b,c,*], Massimo Filippini [c,d]

[a] ZHAW School of Management and Law, Center for Energy and the Environment, Zurich University of Applied Sciences, Bahnhofplatz 12, 8400, Winterthur, Switzerland
[b] Institute for Competitiveness and Communication, Hochschule für Wirtschaft, Fachhochschule Nordwestschweiz, Riggenbachstrasse 16, 4600, Olten, Switzerland
[c] Center of Economic Research (CER-ETH), ETH Zürich, Zürichbergstrasse 18, 8032, Zürich, Switzerland
[d] Institute of Economics, Università della Svizzera italiana, Ex Laboratorio, Office 205 (Level 2) Via Buffi 13, 6904, Lugano, Switzerland

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ABSTRACT

In this paper, we estimate the price elasticity of residential electricity consumption in Switzerland using a unique longitudinal household survey of around 5000 households. The survey contains information on a household's stock of appliances, use of appliances, and various socio-demographic characteristics. Our empirical model is derived from a variant of household production theory that posits electricity demand as being a derived demand for energy services. Based on this, we extend our basic model by using information on energy services, e.g. the amount of washing and the amount of cooking. We also use an instrumental variables approach to obtain consistent estimates of the price elasticity to account for potential endogeneity concerns with the average price. Our results indicate that the short-to medium-run price elasticity is around −0.7. This implies that policy makers concerned about reducing electricity consumption can use pricing policy, with a combination of other policies, to effectively reduce or, at least, stabilise electricity consumption in Switzerland.

1. Introduction

The Fukushima Daiichi nuclear accident on 11 March 2011 led to discussions in Switzerland about the future of nuclear power. The Federal Council decided to suspend the approvals process for new nuclear reactors and, subsequently, decided to permanently ban their construction. Furthermore, it was decided that the five existing nuclear reactors would continue producing electricity until they are gradually phased out with no replacements. The implications of a switch in electricity generation from nuclear to other sources are important for a country like Switzerland which is, at the moment, heavily reliant on its nuclear reactors. Therefore, the Federal Council proposed the *Energy Strategy 2050*, that includes an initial package of measures which aim at reducing the electricity consumption per capita and year compared to consumption in 2000 by 3% by 2020 and 13% by 2035. The Swiss electorate approved the *Energy Strategy 2050* in 2017 that includes the phasing out of nuclear energy.

Estimating the responsiveness of electricity consumption to a price change is important since it has an influence on the design for energy needs in the future and various policy instruments that include pricing and taxation. Obtaining the correct estimates of price elasticities is also important for bottom-up and general equilibrium models used to understand the energy system and the impact of energy policy instruments. There is much debate in this field with regard to the efficacy of a tax or levy on electricity. There is one group who believe that taxes are not an effective instrument due to the very low price responsiveness of consumers to a change in the electricity price in some studies, while another group is in favour of such taxes since the price elasticity in other studies is relatively high.

We ask three research questions in this paper. Firstly, what is the price elasticity of residential electricity consumption? This will enable the design of appropriate pricing policies by utilities and the regulatory authorities to reduce electricity consumption as well as provide a way to forecast demand and plan for generating capacity in the future. Secondly, what is the impact of energy services, such as the number of meals cooked at home and the amount of time spent using personal computers and watching television, on the electricity consumption of a household? Thirdly, how is the price elasticity of demand for electricity affected if we use such measures instead of the usual method of approximating energy services with household and socio-demographic characteristics? This will indicate the difference, if any, between these two methods.

To answer these questions we use data from a large survey of Swiss

* Corresponding author. Institute for Competitiveness and Communication, Hochschule für Wirtschaft, Fachhochschule Nordwestschweiz, Riggenbachstrasse 16, 4600, Olten, Switzerland.

E-mail addresses: boog@zhaw.ch (N. Boogen), souvik.datta@fhnw.ch (S. Datta), massimo.filippini@usi.ch (M. Filippini).

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households conducted in 2015 and 2016 in collaboration with several gas and electric utilities. The survey contains information on a household's stock of appliances, use of appliances, and various socio-demographic characteristics. We also collected the amount of electricity consumed by households in the previous five years, from 2010 to 2015, directly from the electric utility.

Our paper contributes to the existing literature in several ways. Firstly, we use a unique survey of households conducted in Switzerland that includes detailed information on a household's annual electricity consumption, residential and socio-demographic characteristics, its stock of appliances, and its use of these appliances. This provides us with a novel panel data set.[1] The electricity consumption is the actual consumption data reported by the electric utility, and not self-reported by households. Secondly, we base our theoretical model on household production theory that posits electricity demand as being a derived demand for energy services. Using this, we augment our basic models and estimate the electricity demand by using information on energy services, e.g. the number of meals cooked and the amount of washing done by a household. The theoretical model also describes the influence of the price of capital on electricity consumption. We attempt to incorporate this influence by constructing a price for capital by creating an index for appliance stock. Finally, we use an instrumental variables approach using two-stage least squares to account for the possible endogeneity of the average price of electricity and obtain consistent estimates of the price elasticity of residential electricity demand. We find that the price elasticity of residential electricity consumption is about −0.7, higher than many existing studies for Switzerland and this has clear implications for designing energy policy instruments to reduce and modify electricity consumption.

The rest of the paper is organised as follows. In the next section, we provide a short overview of the literature on estimating the own price elasticity of residential electricity demand. In section 3, we provide the motivation for using a modified model of household production to derive a model for estimating electricity demand and a description of our empirical strategy. Section 4 describes the household survey as well as other sources of data. The penultimate section presents the results of our different specifications while the final section has concluding remarks.

2. Literature review

There are a number of studies that estimate long- and short-run price elasticities for residential electricity demand using aggregated data.[2] However, using data at a more disaggregated level can add great detail to the knowledge of consumer response due to the heterogeneity of residential consumers. As noted by Dubin and McFadden (1984), using disaggregated data avoids misspecification error caused by aggregation bias from using aggregate electricity consumption and prices. Table 1 provides an overview of some selected estimated price elasticities for electricity using disaggregated data in the literature. For example, Reiss and White (2005) use a sample of about 1300 Californian households from the Residential Energy Consumption Survey (RECS) for 1993 and 1997 to estimate price and income elasticity using the marginal price and a set of appliances. They find considerable amount of heterogeneity in the estimated elasticities across income and other demographic characteristics. Yoo et al. (2007) use survey data from 380 households in Seoul and a bivariate model to account for sample selection. They find significant sample selection bias and also find that a plasma TV or an air conditioner has a significant positive impact on residential consumption. However, the electricity demand estimated by using the average price appears to be price (−0.25) and income inelastic (0.06). More recently, Ito (2014) and Borenstein (2009) find the elasticity in California to be quite low while Jessoe and Rapson (2014) also find very low arc elasticities for customers in certain areas in the US state of Connecticut.

Table 1
Selected price elasticities using disaggregated data in the literature.

<table>
<tr><th>Author</th><th>Location</th><th>Short-run</th><th>Long-run</th></tr>
<tr><td>International</td><td></td><td></td><td></td></tr>
<tr><td>Tiwari (2000)</td><td>Mumbai (Bombay)</td><td>−0.61 to −0.84</td><td></td></tr>
<tr><td>Halvorsen and Larsen (2001)</td><td>Norway</td><td>−0.433</td><td>−0.442</td></tr>
<tr><td>Reiss and White (2005)</td><td>California</td><td>−0.39</td><td></td></tr>
<tr><td>Yoo et al. (2007)</td><td>Seoul</td><td colspan="2">−0.25</td></tr>
<tr><td>Alberini et al. (2011)</td><td>US</td><td>−0.74</td><td>−0.81</td></tr>
<tr><td>Fell et al. (2014)</td><td>US</td><td>−0.98</td><td></td></tr>
<tr><td>Krishnamurthy and Kriström (2015)</td><td>Cross-country</td><td colspan="2">−0.27 to −1.4</td></tr>
<tr><td>Frondel and Kussel (2019)</td><td>Germany</td><td colspan="2">−0.52</td></tr>
<tr><td>Frondel et al. (2019)</td><td>Germany</td><td>−0.44</td><td>−0.66</td></tr>
<tr><td>Switzerland</td><td></td><td></td><td></td></tr>
<tr><td>Dennerlein and Flaig (1987)</td><td></td><td>−0.2 to −0.4</td><td>−0.4 to −0.6</td></tr>
<tr><td>Dennerlein (1990)</td><td></td><td></td><td>−0.7</td></tr>
<tr><td>Zweifel et al. (1997)</td><td></td><td colspan="2">−0.42 to −0.66</td></tr>
<tr><td>Boogen et al. (2014)</td><td></td><td>−0.4</td><td>−0.4 to −0.6</td></tr>
<tr><td>Krishnamurthy and Kriström (2015)</td><td></td><td></td><td>−0.6</td></tr>
<tr><td>Tilov et al. (2020)</td><td></td><td colspan="2">−0.3</td></tr>
</table>

Conversely, Alberini et al. (2011) find a much higher price response by residential consumers (−0.67 to − 0.86). They use a mix of panel data and multi-year cross-sectional household-level data from over 70,000 households in the 50 largest metropolitan areas in the United States from 1997 to 2007. To correct for a possible mismeasurement problem the average electricity price is instrumented with state-level electricity and gas prices or lagged electricity prices. In contrast to Reiss and White (2005), they find no evidence of significantly different price elasticities for households with electric and gas heating systems. Fell et al. (2014) use monthly data from a consumer expenditure survey collected between 2006 and 2008 to estimate the price elasticity. Using expenditure data and state-level average electricity prices to compute the quantity of electricity consumed they are faced with two possible sources of endogeneity that they solve with a GMM approach. The estimated price elasticity is close to −1 and rather high compared to other cross-sectional studies. They explain this with the fact that they use average price and not marginal price as used in most other studies. Krishnamurthy and Kriström (2015) estimate price elasticity in a cross-country study using data from households in 11 OECD countries for 2011 and find a price elasticity ranging from −0.27 in South Korea to − 1.52 in Australia. Frondel and Kussel (2019) and Frondel et al. (2019) use Germany's Residential Energy Consumption Survey and estimate the price elasticity to be between − 0.44 and −0.66 using panel data estimation techniques.

There are only a few previous studies for Switzerland using disaggregated data. Table 1 also provides an overview of disaggregated studies within Switzerland. Among the first studies using disaggregated

[1] There are several advantages of using panel data over cross-sectional or pure time-series data (see, e.g. Baltagi (2008) and Wooldridge (2002)). Firstly, actors are usually heterogeneous and time-series and cross-section studies cannot control for this heterogeneity. This unobserved heterogeneity could lead to omitted variable bias. Panel data are able to control for these individual and time-invariant factors. Secondly, panel data also offers more variability, more degrees of freedom, more efficiency and less collinearity among the variables. It is well-known that time-series data often have multicollinearity problems.

[2] Studies using aggregated data estimate a price elasticity from −0.07 in the short run and −0.19 in the long run (Blázquez et al., 2013) to − 0.27 in the short run and −0.54 in the long run (Narayan and Smyth, 2005). For Switzerland, Filippini (1999), estimates a long-run price elasticity of −0.3 while Boogen et al. (2017) estimate a short-run price elasticity of −0.3 and a long-run price elasticity of −0.6. Studies using aggregated data estimate, on average, lower price elasticities than studies using disaggregated data.

data were those by Dennerlein and Flaig (1987) and Dennerlein (1990). Dennerlein and Flaig (1987) use pooled cross-section data from almost 6000 households collected with an expenditure survey from 1975 to 1984. This survey also includes information about the ownership of some appliances. The authors estimate the electricity demand as well as two separate probit models for the ownership of electric stove and TV. Moreover, they also control for the ownership of electric stove, electric water and space heating and TV and find short-run elasticities between −0.2 and −0.4 and long-run elasticities of between −0.4 and −0.6. Dennerlein (1990) uses the same database but from 1977 to 1986 and finds slightly higher short-run (−0.5) and long-run (−0.7) elasticities using average prices.

Zweifel et al. (1997) use data from around 1300 households for different years (1989–92) and group them into three different pools depending on whether households have a single-tariff pricing structure, a time-of-use pricing structure and a time-of-use pricing structure by choice. These households are customers of utilities that have either both structures or a time-of-use pricing scheme. For the first group, the price elasticity is very small and not significant. But for the second and third groups the elasticities, estimated by OLS, are significant and −0.66 and −0.59 respectively. Excluding the city of Zürich in the third group reduces the elasticity to −0.42. However, the variation of electricity price in this study is based on only three utility companies and is, therefore, low. Krishnamurthy and Kriström (2015), in their study of a number of OECD countries, use 106 Swiss households and find that the elasticity for Switzerland is around − 0.6. Tilov et al. (2020) use a panel data set of 3880 observations from more than 1400 households between 2015 and 2018 to estimate the price elasticity of Swiss households and find it to be −0.3, on average. Our study is comparable to the analysis by Tilov et al. (2020) since we also focus on Switzerland and our panel data set is from 2010 to 2015. It is interesting to note that our estimates are about double the price elasticity that they find. We think that this difference may be due to the model specification (e.g. the inclusion of energy services and the price of capital stock in our models), the definition of the electricity price variable, and our treatment of the average price of electricity as being endogenous.

As we describe in more detail later, electricity demand is considered to be a derived demand in the sense that electricity is required for services, e.g. for cooking food and for heating water. This demand for energy services to estimate the price elasticity of electricity demand has not been considered by any of the above studies.[3] However, there exists some literature that estimates energy services demand individually, e.g. the demand for heating fuel (Guertin et al., 2003; Fouquet, 2011, 2014), the demand for transport (Fouquet, 2011, 2014), the demand for lighting (Guertin et al., 2003; Fouquet, 2011, 2014) and the appliance load (Guertin et al., 2003). Another drawback that is typically not considered in some of the literature is that the average price is not treated as being endogenous which is caused when, while calculating the average price, the fixed fee is included in the amount spent on electricity.

3. Model and empirical strategy

The residential demand for electricity is considered to be a derived demand since electricity is consumed to provide us with services, e.g. an electric heater providing warmth. We derive the residential electricity demand by using a simplified version of household production theory whereby households combine electricity and capital goods to obtain energy services.[4] We obtain the demand function for electricity, E, as a function of the price of electricity, the price of capital as well as the energy services consumed by a household, after solving a utility maximization problem. The solution can be written as

$$E^{*} = E(P^{E}, P^{K}, S^{*}(P^{E}, P^{K}, M, Z)) \tag{1a}$$

$$= E(P^{E}, P^{K}, M, Z), \tag{1b}$$

where P^E and P^K are the prices of electricity and capital, respectively, S is the amount of energy services consumed, M is the household income and Z is a matrix of socio-demographic and residential characteristics. Eq. (1a) indicates that electricity consumption depends on the electricity price, the price of capital (typically, appliances used by households) and the optimal amount of energy services produced. This implies that, if we can obtain measures of the price variables and the quantity of energy services produced, we will be able to estimate the electricity demand. Usually, the amount of energy services, as in Eq. (1a), is not measured and is, instead, approximated by including residential and socio-demographic characteristics. Therefore, we can also use Eq. (1b) to estimate the electricity demand. This represents electricity consumption as a function of electricity price, price of the stock of appliances, and household income as well as other household characteristics. A potential problem with using household and socio-economic characteristics as proxy measures for energy services is the introduction of unobserved heterogeneity bias. This is due to the fact that household and socio-economic characteristics may not capture all the energy services.

Obtaining an estimate of the price of the stock of appliances is also key to estimating the demand for electricity. We calculate the price index of the appliance stock by using the capacity of the major appliances owned by the household. This is adjusted with the price of the corresponding appliance to determine the price index of the appliance stock.

The previous discussion provides the motivation in terms of the explanatory variables for our econometric model specification. We use a log-log functional form, as is prevalent in the literature. The electricity demand function for household i in year t can then be written as:

$$\log\ E_{it} = \alpha_0 + \alpha_1 \log\ p^E_{it} + \alpha_2 \log\ p^K_{it} + S_{it}\delta + \mu_i + \varepsilon_{it} \tag{2a}$$

$$\log\ E_{it} = \alpha_0' + \alpha_1' \log\ p^E_{it} + \alpha_2' \log\ p^K_{it} + M_{it}\delta' + Z_{it}\gamma' + \mu_i' + \varepsilon_{it}', \tag{2b}$$

where α_1 and α_1' are the parameters to be estimated for the price of electricity p^E_{it}, α_2 and α_2' are the parameters to be estimated for the price of household appliances p^K_{it}, δ is a vector of parameters to be estimated for energy services S_{it}, α_3' is the parameter to be estimated for household income M_{it}, γ' is a vector of parameters to be estimated for household characteristics Z_{it}, μ_i and μ_i' control for the household-specific unobserved heterogeneity, and ε_{it} and ε_{it}' are the usual error terms, assumed to be independently and identically distributed. An advantage of using a log-log specification is that the coefficient of electricity price, e.g., α_1, is easily interpreted as the price elasticity of electricity demand. Assuming that α_1 is negative, a 1% increase in electricity price will reduce electricity consumption by α_1%, *ceteris paribus*.

The method to calculate the electricity price is crucial to estimate the price elasticity of electricity. While the literature on this is substantial, the main approaches can be divided into two strands. In the first approach, Nordin (1976) suggests using the marginal price (and subtracting the fixed fee from the income in case there is a two-part tariff). The second approach is to use the average price (Shin, 1985), calculated by dividing the electricity bill with the quantity of electricity consumed.

[3] Our approach is different from the end-use estimates for electricity consumption of different appliances. Early literature on end-use estimation using conditional demand analysis include studies by Parti and Parti (1980) and Aigner et al. (1984) while later studies using metered electricity consumption include studies by Bartels and Fiebig (2000) and Marit Dalen and Larsen (2015).

[4] See Deaton and Muellbauer (1980) for a description of household production theory and Dubin (1985), Flaig (1990) and Filippini (1999) for an application to electricity demand analysis. Note that there is no labour input in this version of the household production model.

In micro-level data, two-part tariffs imply that the average price depends on the amount consumed and are, therefore, endogenous with one another. In our case, the presence of two-part tariffs in most utilities in our sample means that we need to use the marginal price and fixed fee to calculate the electricity bill by multiplying the electricity consumption with the marginal price and then adding the fixed fee. We then calculate the average price by dividing the electricity bill with the quantity of electricity consumed.

The advantage of using the marginal price over the average price is its exogeneity, i.e. the marginal price of electricity will affect electricity consumption but not the other way round. Since the average price is calculated by dividing spending on electricity bill, that usually includes a fixed fee, with the quantity consumed, there exists a problem of simultaneous causality which leads to the average price being an endogenous explanatory variable.[5] In a different context, Taylor et al. (2004) use marginal as well as average price to estimate residential water demand and find the estimate of elasticity to be biased upward towards unity in the average price specification due to the presence of a fixed charge in average price (see Frondel and Kussel (2019) for an application). However, the bias due to fixed fees is small according to Baker et al. (1989). As discussed in the literature, the average price is probably more important than the marginal price since households are more concerned about their total electricity bill rather than the price of electricity at the margin (e.g. Shin (1985), Borenstein (2009), Fell et al. (2014) and Ito (2014)). An additional issue is that there is little variation in the marginal prices within each utility. Since we do not observe a household's tariff structure but impute it from the respective utility's most common tariff structure, the variation in marginal prices does not exist within a utility but only across utilities. We, therefore, use the average price in our analysis and use marginal prices as robustness checks.

A further concern is the problem of measurement error in our electricity price variable. As mentioned above, the tariff structure that we use to calculate the average price is obtained from the respective utility and reflects the most common tariff. A utility may have more than one tariff structure in place, e.g. a "green" tariff from new renewables as well as a normal tariff. Since we cannot identify the tariff structure from the survey our calculated average price might be affected by measurement error. We, therefore, use the potential endogeneity arising from simultaneity and measurement error in the average price to motivate our use of instrumental variables.

We have two IV models in which the average price is the endogenous variable. We use two exogenous price variables, described below in section 4.2, as instruments for the average price. For the rest of our analysis, we estimate Equations (2a) and (2b) where the parameters of interest are the estimates of α_1 and α_1', i.e. the price elasticities of residential electricity consumption in Switzerland. Our objective is to estimate these elasticity parameters by taking into account the possible endogeneity of the average price.

We make use of annual observations spanning over 5 years and are using static models. As a result, we are unable to clearly distinguish between short-run and long-run nature of the reported elasticity value. Nevertheless, our fixed- and random-effects (static) panel data estimators, both with and without the IV, exploit the within variation of the data. Van den Doel and Kiviet (1994, 1995) also conclude that, under certain conditions, static estimators will underestimate the long run coefficients when the within estimator is used. Hence, based on Houthakker (1965), we can interpret the reported elasticity values to be of short-to medium-run in nature. In the long run, households can be expected to have more opportunities to invest in more energy-efficient systems, so the long-run elasticity may be larger in absolute value.

[5] For a more detailed discussion on this issue see, e.g. Krishnamurthy and Kriström (2015).

4. Data

The primary data come from a large household survey conducted in 2015–2016 in collaboration with several gas and electricity utilities while we use additional data from the Schweizerische Agentur für Energie Effizienz (SAFE) and comparis, a Swiss price comparison website. The data are described below while Table 2 provides the summary statistics of all the variables.

4.1. Household survey

We use data from a large household survey performed in cooperation with seven Swiss utilities.[6] Utilities operating in urban and suburban areas were selected in order to get a sample of households as homogeneous as possible in terms of environment. The participating utilities invited either all or a sub-sample of their customers to take part in an online survey. If sub-samples of customers were drawn, all household

Table 2
Summary statistics.

Variable	Mean	Std. Dev.	Min.	Max.	N
Electricity consumption (kWh)	4130.52	4648.57	1	106108	20637
Average price (expenditure utility)	22.25	73.15	0	8927	20637
Average marginal price (median share)	18.34	2.43	13.85	24.32	20637
Average marginal price (own share)	18.37	2.81	9.70	25.53	20637
Price of appliance stock (CHF/Watt)	0.59	0.17	0.14	13.18	20637
Marginal price (peak)	20.98	1.79	18.11	25.53	20637
Marginal price (off-peak)	13.28	2.24	9.46	18.92	20637
Marginal price (single tariff)	20.16	2.10	16.38	24.32	16080
Marginal price of gas	8.52	1.42	6.16	11.66	18925
Number of cooked meals	8.42	3.45	0	14	20637
Number of washing services	6.15	5.24	0	36	20637
Number of TV and PC hours	6.57	5.29	0	52	20637
Number of shower services	10.15	5.80	0	22	20637
Indicator for time-of-use pricing	0.63		0	1	20637
Cooling degree days	198.59	112.21	51.4	458.6	20637
Heating degree days	2884.72	463.26	1925.6	3670.3	20637
Household size	2.37	1.20	1	6	19630
Indicator for single-family house	0.37		0	1	20637
Home owner	0.52		0	1	20637
Income <6000 CHF/month	0.25		0	1	20637
Income between 6000 and 12000 CHF/month	0.42		0	1	20637
Income >12000 CHF/month	0.16		0	1	20637
Number of rooms	4.01	1.28	0	6	20637
Indicator for children	0.24		0	1	20637
Indicator for elderly	0.30		0	1	20637
Share of females	0.52	0.28	0	1	20376

[6] The seven utilities are Aziende Industriali di Lugano (AIL), IBAarau (IBA), Stadtwerk Winterthur (SW), Energie Service Biel/Bienne (ESB), Energie Wasser Luzern (EWL), Energie Wasser Bern (EWB), and Industrielle Werke Basel AG (IWB) that operate in (and the surrounding areas of) Lugano, Aarau, Winterthur, Biel/Bienne, Lucerne, Bern and Basel, respectively. Aarau, Basel, Bern, Winterthur and Lucerne are in the German-speaking region, Lugano is in the Italian-speaking region while Biel/Bienne is bilingual (German- and French-speaking).

customers had the same probability of being in the sample. The invitation letter was sent either separately or accompanying a bi-monthly, quarterly or yearly electricity or gas bill. The survey collected details on household and dwelling attributes from 2010 to 2014. Annual electricity consumption data between 2010 and 2014 were also collected from the respective utilities using the unique customer ids for households that provided consent. More details on the survey and its organisation are provided in Blasch et al. (2018).

The survey collected several attributes of the households - characteristics like size and age of the building, socio-economic information like type of household, household size and the level of income, the stock of appliances and type of installed space and water heating systems, among other things. The detailed list of variables that we use in our analysis is in Table 2. For our purpose, we consider the relevant panel of households for which we have valid electricity consumption data, around 5000 unique households.

4.2. Electricity price

Apart from the survey, we also use electricity price data directly from the electric utilities. The average price of electricity is calculated by multiplying the electricity consumption of the household with the marginal price faced by the household, adding the fixed fee (if any) and dividing this total cost by the total electricity consumption.[7] There has been considerable debate as to whether consumers respond to the marginal price or the average price when the tariff structure consists of fixed fees and/or block pricing.

Shin (1985) states that households find it easier to calculate the average price from the electricity bill rather than the block marginal price. Borenstein (2009) and Ito (2014) also use household-level information to argue that households respond to average price. In our study, we follow their approach and use the average price to estimate the price elasticity. Of course, we should be aware that this variable is endogenous due to the presence of the fixed fee. Therefore, we correct for this endogeneity by using instrumental variables that will provide consistent estimates of the price elasticity. Therefore, we need variables that will satisfy the relevance and exclusion criteria for instruments. In our case, the instrument should be correlated with the average price to satisfy the relevance condition but affect the electricity consumption only through its effect on average price to satisfy the exclusion criterion.

We use two instrumental variable models. In the first model, we follow the approaches of Olmstead (2009) and Wichman et al. (2016), among others, and use the marginal peak and off-peak electricity prices as instruments. These instruments are frequently used because the marginal prices are generally determined by the electric utilities in accordance with the regulator and, therefore, exogenous to the demand. We estimate a second IV model where, as an instrument for the average electricity price faced by the households, we follow Grafton et al. (2011) and Filippini and Kumar (2020) and use a local average price variable computed considering the mean of the average prices faced by all the other dwellings located within a postcode area. This means that if we have N households living within a postcode, we use the average value over the $N-1$ other households in the same postcode. This price measure is exogenous to the household but represents the average price of the area. These additional results are expected to not only account for some of the typical estimation issues related to the endogeneity of energy price variables but also serve as a robustness check.

4.3. Price of appliances

Following Diewert (1974) and Thomas (1987), we calculate the "user cost" of appliances that reflects the price of services obtained from a durable good even though it has been purchased by the household. Let us define this rental price or user cost of household appliances as P_k'. Thomas (1987, p. 26–27) defines the user cost as the difference between the purchase at the beginning of one period and the discounted price at the beginning of the next period after taking depreciation into account:

$$P'_{k,t} = P_{k,t} - \frac{(1-\delta_{lifetime})P_{k,t+1}}{1+r_{t,canton}} \tag{3}$$

where $P_{k,t}$ is the price of each appliance k [8], $\delta_{lifetime}$ is the annual rate of depreciation and $r_{t,canton}$ is the annual opportunity cost of capital. The interest rate $r_{t,canton}$ consists of cantonal mortgage interest rates[9].

We can rewrite Equation (3) as:

$$P'_{k,t} = \frac{(\delta_{lifetime}\cdot P_{k,t+1}) + (r_{t,canton}\cdot P_{k,t}) + (P_{k,t} - P_{k,t+1})}{1+r_{t,canton}} \tag{4}$$

For simplicity, we assume that the initial value of the appliance is the same as in the next time period ($t+1$), as there are no efficiency losses during the lifetime. This means that $P_{k,t} = P_{k,t+1}$. At the end of the appliance's lifetime the value will be zero instantly.[10] Therefore, we can simplify Equation (4) to:

$$P'_{k} = \frac{(\delta_{lifetime} + r_{t,canton})\cdot P_k}{1+r_{t,canton}} \tag{5}$$

Using the rental price of the eleven major appliances and an index of estimated capacity we can create a *price per installed capacity (in Watt)* for each household.[11] The price per installed capacity is defined as:

$$\begin{aligned} PI_i &= \frac{\sum_{k=1}^{11}(\text{Rental Price of Appliance}_{i,k})}{\sum_{k=1}^{11}(\text{Estimated Capacity}_{i,k})} \\ &= \frac{\sum_{k=1}^{11}P'_k}{AI_i}. \end{aligned} \tag{6}$$

The price of capital, as calculated above, has possible measurement issues since the information on appliances is very broad and there could be heterogeneity within various categories.

4.4. Energy services

The household survey also contains information on some activities by households with regard to energy use in the week prior to the survey being undertaken. We combine energy use into four broad categories, *viz.*, the amount of washing, the amount of meals cooked at home, the number of hours spent on entertainment and the amount of hot water services. We combine the use of a clothes washer, tumble dryer and dehumidifier as representing the amount of washing. The amount of meals cooked at home is defined as the sum of breakfasts, lunches and dinners made at home. We obtain the number of hours spent on entertainment by adding the hours spent on a personal computer and on watching television. Hot water services are calculated by adding the

[7] While a household may choose to use a particular tariff structure, e.g. electricity from renewables, we do not have this information and so consider the most common tariff that is provided by the respective electric utility.

[8] These price estimates were also provided to us by SAFE. Similar to the measurement of the capacities for the 11 major appliances, these price estimates are approximate prices of the corresponding appliances by dividing the appliances into their vintage and size.

[9] The interest rate figures were provided by comparis, a Swiss price comparison website. The values for $\delta_{lifetime}$ and $r_{t,canton}$ are in Tables 6 and 7 in the appendix.

[10] There is also a simplified version of the user cost that assumes that the appliance is not sold in the next period but is kept till its value depreciates to zero. We have estimated our specifications using this version and the results are very similar.

[11] We refer to the index of estimated capacity as the appliance index. Its calculation is described in greater detail in the Appendix.

number of showers and baths taken. Lighting is also an important component of energy services. However, since we do not have information on the number of hours a household's lights are switched on, we use the number of rooms as an approximation.

5. Results and discussion

We now present the results obtained by estimating models based on Equations (2a) and (2b). The outcome variable in all models is the (natural) logarithm of the annual electricity consumption by the households in our sample, while the average price of electricity is our primary regressor of interest[12].

In Table 3 we report the estimation results for a fixed effects model, FE(1), a random effects model with Mundlak's adjustment terms for the time-variant controls, REM(1), and two models using instrumental variables to account for the possible endogeneity of the average price, IV (1) and IV(2).[13] A feature of Mundlak's adjustment is that it allows for the correlation of unobserved variables with observed covariates in a random effects setting, and explicitly models this heterogeneity bias by also including group means of the time-varying covariates in the estimation (Mundlak, 1978; Bell and Jones, 2015). The results also hold for an unbalanced panel (Wooldridge, 2019).

As Table 3 shows, the magnitude of the own price elasticity of electricity demand is around −0.7. The results are quite consistent across FE(1), REM(1), and IV(1). The point estimate for IV(2) is lower, around − 0.5. However, the confidence interval for model IV(2) is quite large and this suggests that IV(2) may not be precisely estimated. The first-stage *F*-statistic and the endogeneity test also indicate that model IV (2) is not as robust as model IV(1). The signs and magnitudes of the coefficients of the covariates across all the models are comparable (except for the coefficient of heating degree days in model IV(2)). The coefficient of the price of gas, a substitute of electricity, is positive. An increase in the price of gas will lead to an increase in the consumption of electricity. Weather also has an influence on electricity consumption, as do larger households or families. The REM(1) model also produces estimates of energy services. The results show that washing and entertainment (in the form of watching TV and using computers) appear to have an influence on the electricity consumption, while cooking and showering do not appear to have significant effects. Income does not appear to have a statistically significant impact on electricity consumption. This is probably due to the inclusion of other measures like the number of rooms, the ownership, and if the household lives in a single-family house, all of which are positively correlated with the electricity consumption. Fig. 1 provides an overview of the point estimates and the confidence intervals at the 90%, 95% and 99% levels for the coefficient of average price of electricity.

We test for the potential endogeneity of the average electricity price for the models in columns IV(1) and IV(2) and find that the null hypothesis of the average electricity price being exogenous can be rejected for IV(1) at the 1%, 5% and 10% levels, though not for IV(2) even at the 10% level.[14] The evidence for the relevance of our instruments is provided by the first-stage *F*-statistic. Since the *F*-statistics of the first stages

Table 3
Regression models of long-run log electricity demand with the average price.

	FE(1)	REM(1)	IV(1)	IV(2)
(Log) Average price	-0.74^{a}	-0.74^{a}	-0.67^{a}	-0.46^{a}
	(0.02)	(0.01)	(0.04)	(0.17)
(Log) CHF/Watt	−0.01	−0.02	−0.01	−0.01
	(0.03)	(0.03)	(0.03)	(0.03)
(Log) Marginal price of gas	0.22^{a}	0.23^{a}	0.23^{a}	0.26^{a}
	(0.04)	(0.04)	(0.04)	(0.04)
Indicator for time-of use pricing	0.04^{c}	0.04^{b}	0.05^{b}	0.09^{b}
	(0.02)	(0.02)	(0.02)	(0.04)
(Log) Cooling degree days	0.34^{a}	0.34^{a}	0.31^{a}	0.21^{b}
	(0.03)	(0.02)	(0.03)	(0.09)
(Log) Heating degree days	0.65^{a}	0.65^{a}	0.55^{a}	0.26
	(0.12)	(0.11)	(0.12)	(0.27)
(Log) Number of cooked meals		0.005		
		(0.017)		
(Log) Number of washing services		0.11^{a}		
		(0.01)		
(Log) Number of TV and PC hours		0.12^{a}		
		(0.01)		
(Log) Number of shower services		0.02		
		(0.01)		
Income less than 6000 CHF/month		0.02		
		(0.02)		
Income between 6000 and 12000 CHF/ month		0.01		
		(0.02)		
Income greater than 12000 CHF/month		0.02		
		(0.02)		
Household size	0.08^{a}	0.08^{a}	0.08^{a}	0.09^{a}
	(0.01)	(0.01)	(0.01)	(0.01)
Number of rooms		0.10^{a}		
		(0.01)		
Indicator for single-family house		0.22^{a}		
		(0.02)		
Home owner		0.08^{a}		
		(0.02)		
Indicator for children		−0.01		
		(0.02)		
Indicator for elderly		0.04^{b}		
		(0.02)		
Share of females		0.01		
		(0.02)		
Intercept	2.46^{a}	-88.32^{a}		
	(0.90)	(6.17)		
Mundlak terms	No	Yes	No	No
Observations	19743	19511	19169	19005
Households	4997	4934	4423	4338
Overall R^2	0.95	0.72		
F-statistic of first stage			292.83	71.27
p-value of endogeneity test			0.01	0.19

Notes: The dependent variable in all models is the natural logarithm of the annual household electricity consumption. The seven utilities included in all the models are AIL, ESB, EWB, EWL, IBA, IWB, and SW. Heteroscedasticity-robust standard errors are in parentheses. Significance at the 1%, 5% and 10% levels are denoted by ^{a}, ^{b}, and ^{c}, respectively. Coefficient estimates of the Mundlak terms are reported in Table 10 in the Appendix.

reported in Table 3 exceed the critical value, we conclude that the instruments do not appear to be weak. The coefficients of the instruments in the first stage, reported in Table 4, are significant and have the expected positive sign which means that the peak and off-peak marginal prices and the average price of neighbours are positively correlated with the average electricity price faced by the household. The value of the *F*-statistic in the first stage is quite high. This suggests that the bias of the IV estimator vanishes as the *F*-statistic becomes large (Angrist and Pischke, 2009, p. 208). Since column IV(1) has two instruments we test for weak instruments using the Cragg-Donald statistic (Cragg and Donald, 1993). The Cragg-Donald statistic of 292.83 easily exceeds the Stock and Yogo critical values.

The coefficient estimates for the rental price of capital stock are not statistically significant. Most coefficients of household characteristics are significant and show the expected sign. Increasing the household

[12] We have also, for comparison, estimated our models with the marginal price of electricity as our primary regressor of interest. The results are presented in Table 9 in the Appendix. As discussed previously, we think that there are two reasons why we do not believe that the marginal price is suitable. First, is the classical argument made by Shin (1985), Borenstein (2009), and Ito (2014). Secondly, since we have a small number of utilities in our data set, the variation in the marginal price is not sufficiently large to make robust conclusions.

[13] A random effects model with Mundlak's adjustment is also known as a correlated random effects model. The correlated random effects models in our analyses are estimated in Stata/SE 13.1 using the `mundlak` command (Perales, 2013).

[14] We use the `endog()` option in Stata/SE 13.1's `xtivreg2` command (Schaffer, 2005).

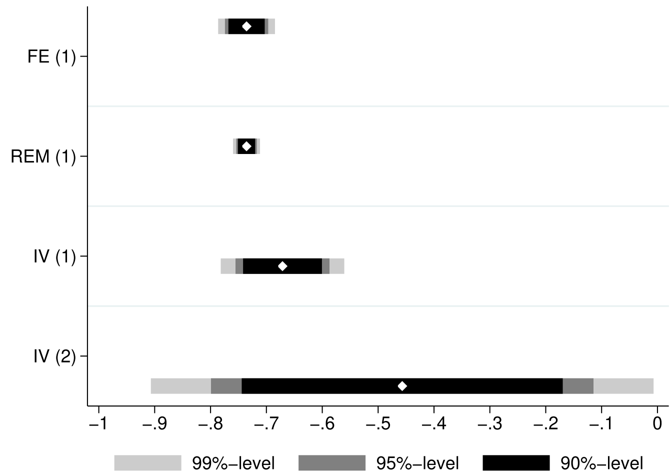

Fig. 1. Point estimates of the coefficients of the own price elasticity of electricity demand from Table 3 with 99%, 95%, and 90% confidence intervals.

Table 4
First stage regression of long-run log electricity demand.

	IV(1)	IV(2)
(Log) Marginal off-peak price	0.19[a]	
	(0.04)	
(Log) Marginal peak price	0.53[a]	
	(0.08)	
Average price of neighbours		0.028[a]
		(0.003)
(Log) CHF/Watt	0.01	−0.01
	(0.03)	(0.03)
(Log) Marginal price of gas	−0.25[a]	−0.14[a]
	(0.03)	(0.03)
Indicator for time-of-use pricing	−0.15[a]	−0.19[a]
	(0.02)	(0.02)
(Log) Cooling degree days	0.59[a]	0.47[a]
	(0.02)	(0.02)
(Log) Heating degree days	0.84[a]	1.40[a]
	(0.10)	(0.10)
Household size	−0.02[a]	−0.02[a]
	(0.01)	(0.01)
Observations	19169	19005
Adjusted R^2	0.90	0.92

Notes: The dependent variable is the natural logarithm of the average price of electricity. Standard errors are in parentheses. Significance at the 1%, 5% and 10% levels are denoted by [a], [b], and [c], respectively.

size, number of rooms and being a home owner have, as expected, positive and significant effects on the electricity consumption. Most coefficient estimates are very similar across the different models. The strong statistical significance for the household characteristics variables suggests a large degree of heterogeneity among households that, in turn, indicates the advantage of using disaggregated data.

One of the objectives in this paper is to compare the price elasticity of electricity demand between models that consider only household and residential characteristics and models that include energy services. If we compare the elasticity estimates of the models with energy services with the other models, as shown in Fig. 1, we notice that the price elasticity using energy services and the price elasticity using only household and residential characteristics as a proxy for energy services are quite similar. Therefore, we can conclude that household and residential characteristics, as used by previous researchers in this field, are good proxy measures for energy services. Another objective is to use a novel panel data set to estimate the household price elasticity of electricity consumption in Switzerland, since there is only one other study that analyses this (Tilov et al., 2020). Our estimates, using another data set, are higher than their average estimate and more in line with some other studies (see Table 1). Given that Tilov et al. (2020) and our study are quite similar in terms of the country and the years analysed, it is interesting to note that our estimates are about double the price elasticity that they find. We can only speculate about the differences that, we think, arise from the main regressor of interest, the price of electricity, being calculated differently: we use the average price as calculated from the tariff rate and the amount of electricity consumed, as used by several other studies. We also use energy services in our models and some of the variables are not common to both analyses. As mentioned by Krishnamurthy and Kriström (2015), the high price elasticities that they get is closer to some estimates in the older literature, than most of the current literature. Our estimates are similar to the estimates that Krishnamurthy and Kriström (2015) get for Switzerland, though their estimates are long-run while ours are short-to medium-term.

6. Conclusions and policy implications

The future direction of climate and energy policies has been the subject of much political debate. It is, therefore, important to obtain a measure of the responsiveness of households to changes in the price of electricity. This will enable policy makers and electric utility companies to design appropriate pricing policies to modify consumer behaviour. Obtaining the correct estimates of price elasticities is also important for bottom-up and general equilibrium models used to understand the energy system and the impact of energy policy instruments.

In this paper, we estimate the price elasticity of residential electricity consumption in Switzerland using a unique panel data set from a large household survey conducted in 2015 and 2016. The data set includes detailed information on a household's annual electricity consumption, residential and socio-demographic characteristics, its stock of appliances, and its use of these appliances. We specify our empirical model of electricity demand, based on household production theory, as the derived demand for energy services. Therefore, we augment a more traditional model of electricity demand by using information on energy services, e.g. the number of meals cooked and the amount of washing done by a household. In addition, we correct for the endogeneity of average price by using an instrumental variables approach to obtain consistent estimates of the price elasticity. We find that, after correcting for the endogeneity of average price, the price elasticity of residential electricity consumption is around −0.7.[15] Our study provides new empirical evidence using a unique household survey. Moreover, our study improves upon previous studies by using an instrumental variables approach for the average price as well as augmenting the models by incorporating information on the use of energy services. We find that the results using only the household and residential characteristics and the results using some energy services instead of all the household and residential characteristics are very similar. This leads us to conclude that household and residential characteristics, as used by previous researchers in this field, are good proxy measures for energy services.

Our estimates indicate that the price elasticity of electricity demand in Switzerland is higher (in absolute value) than similar studies, since our fixed effects estimates are indicative of short-run elasticities (Houthakker, 1965). Our analysis may also be considered to be short-to medium-run since we use a static panel. The price elasticity of demand we obtain is much higher than the elasticity obtained by Tilov et al. (2020). Therefore, an incentive tax on electricity might be much more effective than what policy makers currently assume. There is currently, no levy or tax planned on electricity since most of Switzerland's electricity is produced from non-fossil fuels. However, increasing the efficient use of electricity is crucial for the planned nuclear phase-out as well as the decarbonisation process. An exception in Switzerland, in

[15] This estimate is valid for households without electric heating systems. The share of Swiss households with heating systems is only around 6% (Prognos, 2008).

terms of a levy or tax on electricity, is the city of Basel. Basel introduced a tax on electricity in 1999 to increase the conservation of electricity. Krebs and Luechinger (2020) analyse the impact of this tax and conclude that, even though they find a statistically insignificant effect of the tax of -2.7 to -1.9%, they "are convinced that electricity taxes can be effective." Therefore, policy makers concerned about reducing electricity consumption can use pricing policy, with a combination of other policies, to effectively reduce or, at least, stabilise electricity consumption in Switzerland. However, there is some evidence, as shown by Tilov et al. (2020), that taxes could lead to issues with equity and policy makers may need to alleviate the impact of such electricity taxes on more vulnerable groups in society by redistributing the tax revenue.

CRediT authorship contribution statement

Nina Boogen: Conceptualization, Methodology, Formal analysis, Writing- Reviewing and Editing. **Souvik Datta:** Conceptualization, Methodology, Formal analysis, Writing- Original draft preparation, Writing- Reviewing and Editing. **Massimo Filippini:** Conceptualization, Methodology, Writing- Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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A Appendix.

Appliance index

We construct an appliance index that aggregates the appliances owned by a household into one index that can be compared across the households in our survey. We do this by using a measure of the approximate power used by the major household appliances that we refer to as the "estimated capacity". The estimated capacity of the 11 major appliances is obtained by dividing the appliances into their vintage (older than 5 or 10 years) and size. The estimated capacity of an appliance is the average power used by the appliance while in use.[16] Electric boiler capacities are estimated by using the number of people in a particular household. See Table 5 for the detailed appliance characteristics used for the index.

We define the appliance index of household i, AI_i, as the sum of the estimated capacities, in Watts, of the 11 appliances:

$$AI_i = \sum_{k=1}^{11} \text{Estimated Capacity}_{i,k} \tag{7}$$

where k refers to appliance k. The estimated capacity is a function of the vintage, size and, for electric boilers only, household size.

Tables 6 and 7 present the depreciation rate ($\delta_{lifetime}$) and the interest rate ($r_{t,canton}$) used in Equation (5), respectively.

Table 5
Capacity characterisation of appliances.

Appliance	Age class	Other characteristics
Stove	Up to 5 yrs/6–10 yrs/10 + yrs	
Oven	Up to 5 yrs/6–10 yrs/10 + yrs	
Refrigerator	Up to 5 yrs/6–10 yrs/10 + yrs	normal/combined with freezer
Freezer	Up to 5 yrs/6–10 yrs/10 + yrs	
Dishwasher	Up to 5 yrs/6–10 yrs/10 + yrs	
Washing machine	Up to 5 yrs/6–10 yrs/10 + yrs	
Tumble dryer	Up to 5 yrs/6–10 yrs/10 + yrs	
Television		CRT/LCD
Personal computer		Desktop/Laptop
Electric boiler		Household size

[16] The estimated reference capacities (in Watts) have been provided by the Schweizerische Agentur für Energie Effizienz (SAFE).

Table 6
Depreciation rates used for different appliances.

Appliance	Lifetime (years)	Depreciation rate
Personal computer, television	5	0.2
Dishwasher, microwave	10	0.1
Clothes washer, tumble dryer, refrigerator	12	0.08
Boiler, stove	20	0.05

Table 7
Annual interest rates for different locations.

Name of utility	Interest rate
Aziende Industriali di Lugano (AIL)	3.50%
Energie Service Biel/Bienne (ESB)	3.35%
Energie Wasser Bern (EWB)	3.35%
Energie Wasser Luzern (EWL)	3.49%
IBAarau (IBA)	3.35%
Industrielle Werke Basel AG (IWB)	3.45%
Stadtwerk Winterthur (SW)	3.34%

Additional Tables

Table 8
Summary statistics (within and between variation) of selected variables.

Variable		Mean	Std. Dev.	Min.	Max.
Electricity consumption (in kWh)	*(overall)*	4830.53	14629.38	1.00	959544.00
	(within)		2546.61	−140024.67	193147.33
	(between)		13155.71	1.00	771227.20
Average price	*(overall)*	20.32	65.76	0.00	8927.00
	(within)		15.48	−1475.40	1079.18
	(between)		114.81	0.00	8927.00
Marginal price (own share)	*(overall)*	19.14	3.60	13.85	27.61
	(within)		1.53	13.13	25.14
	(between)		3.26	16.06	25.01
Marginal price (median share)	*(overall)*	18.37	2.81	9.70	25.53
	(within)		1.25	9.97	24.73
	(between)		2.53	12.24	24.84
Price of appliance stock (CHF/Watt)	*(overall)*	0.59	0.37	0.13	17.40
	(within)		0.08	−8.90	3.03
	(between)		0.36	0.17	16.07
Marginal price (peak)	*(overall)*	22.59	3.80	18.11	32.74
	(within)		1.35	19.03	26.22
	(between)		3.56	18.70	32.05
Marginal price (off-peak)	*(overall)*	14.66	3.81	9.46	23.33
	(within)		1.46	10.68	18.96
	(between)		3.52	11.50	21.59
Marginal price (single tariff)	*(overall)*	21.87	3.86	16.38	30.46
	(within)		1.45	18.25	25.55
	(between)		3.57	18.58	29.95
Marginal price of gas	*(overall)*	9.21	3.46	6.16	24.35
	(within)		0.65	7.80	10.37
	(between)		3.40	6.85	23.61
Number of cooked meals	*(overall)*	8.20	3.38	0.00	14.00
	(within)		0.00	8.20	8.20
	(between)		3.38	0.00	14.00
Number of washing services	*(overall)*	5.46	5.07	0.00	36.00
	(within)		0.00	5.46	5.46
	(between)		5.07	0.00	36.00
Number of TV and PC hours	*(overall)*	6.50	5.44	0.00	52.00
	(within)		0.00	6.50	6.50
	(between)		5.44	0.00	52.00
Number of shower services	*(overall)*	10.18	5.66	0.00	22.00
	(within)		0.00	10.18	10.18
	(between)		5.66	0.00	22.00
Indicator for time-of-use pricing	*(overall)*	0.52	0.50	0.00	1.00
	(within)		0.07	−0.28	1.32
	(between)		0.50	0.00	1.00

Table 9
Regression models of long-run log electricity demand with marginal prices.

	FE(2)	FE(3)	REM(2)	REM(3)
(Log) Marginal price (own share)	−0.35[a]		−0.34[a]	
	(0.05)		(0.04)	
(Log) Marginal price (median share)		−0.47[a]		−0.47[a]
		(0.04)		(0.04)
(Log) CHF/Watt	0.01	−0.01	−0.01	−0.03
	(0.04)	(0.04)	(0.04)	(0.04)
(Log) Marginal price of gas	0.44[a]	0.41[a]	0.45[a]	0.42[a]
	(0.05)	(0.05)	(0.04)	(0.04)
Indicator for time-of-use pricing	0.15[a]	0.13[a]	0.15[a]	0.13[a]
	(0.04)	(0.04)	(0.02)	(0.02)
(Log) Cooling degree days	−0.03	−0.09[a]	−0.03	−0.09[a]
	(0.03)	(0.03)	(0.03)	(0.03)
(Log) Heating degree days	−0.38[a]	−0.04	−0.38[a]	−0.04
	(0.13)	(0.12)	(0.14)	(0.13)
(Log) Number of cooked meals			0.09[a]	0.05[a]
			(0.02)	(0.02)
(Log) Number of washing services			0.15[a]	0.15[a]
			(0.01)	(0.01)
(Log) Number of TV and PC hours			0.16[a]	0.17[a]
			(0.01)	(0.01)
(Log) Number of shower services			0.08[a]	0.06[a]
			(0.02)	(0.02)
Income less than 6000 CHF/month			0.06[a]	0.04[b]
			(0.02)	(0.02)
Income between 6000 and 12000 CHF/month			0.04[b]	0.03
			(0.02)	(0.02)
Income greater than 12000 CHF/month			0.03	0.02
			(0.02)	(0.02)
Household size	0.10[a]	0.09[a]	0.10[a]	0.09[a]
	(0.01)	(0.01)	(0.01)	(0.01)
Number of rooms			0.11[a]	0.12[a]
			(0.01)	(0.01)
Single-family house			0.26[a]	0.31[a]
			(0.02)	(0.02)
Home owner			0.10[a]	0.10[a]
			(0.02)	(0.02)
Indicator for children			0.04	−0.01
			(0.03)	(0.03)
Indicator for elderly			0.08[a]	0.05[b]
			(0.02)	(0.02)
Share of females			−0.05	−0.05[c]
			(0.03)	(0.03)
Intercept	11.01[a]	9.06[a]	−36.75[a]	17.78[b]
	(0.98)	(0.97)	(7.64)	(7.26)
Mundlak terms	No	No	Yes	Yes
Observations	18718	19743	18496	19511
Overall R^2	0.92	0.93	0.52	0.56

Notes: The dependent variable in all models is the natural logarithm of the annual household electricity consumption. The seven utilities included in all the models are AIL, ESB, EWB, EWL, IBA, IWB, and SW. Heteroscedasticity-robust standard errors are in parentheses. Significance at the 1%, 5% and 10% levels are denoted by [a], [b], and [c], respectively. Coefficient estimates of the Mundlak terms are reported in Table 10 in the Appendix.

In Table 9, we estimate our models with the marginal price of electricity as our primary regressor of interest. The table shows that the own price elasticity of electricity demand is lower than the models in Table 3. The fixed effects and random effects models, FE(2) and REM(2), respectively, indicate a very low price elasticity of around − 0.3. The regressor variable of interest is the marginal price of electricity with own shares. The estimated price elasticities in models FE(3) and REM(3) are around − 0.5 and lie between the models estimated in Table 3 and models FE(2) and REM(2). The regressor variable of interest is again the marginal price of electricity, but with median shares. The signs and magnitude of the covariates across all the models are comparable as in Table 3 (except for the coefficients of heating degree days in models FE(3) and REM(3)). The coefficient of the price of gas, a substitute of electricity, is positive. However, the magnitude is twice as much as the estimated coefficients in Table 3. An increase in the price of gas will lead to an increase in the consumption of electricity. Weather also has an influence on electricity consumption, though the signs are opposite to what we expect and observe in Table 3. Larger households or families also tend to increase the electricity consumption. The REM(1) model also produces estimates of energy services. Models REM(2) and REM(3) also provide estimates of energy services. The results show that washing and entertainment (in the form of watching TV and using computers) as well as cooking and showering have a positive correlation with the electricity consumption. Income, in models REM(2) and REM(3), is also positively correlated with electricity consumption. Other covariates like the number of rooms, home ownership, and an indicator for a single-family house are also positively correlated with the electricity consumption. Fig. 2 provides an overview of the point estimates and the confidence intervals at the 90%, 95% and 99% levels for the coefficient of marginal price of electricity. One of the issues in these models is that the marginal price exhibits very low variation.

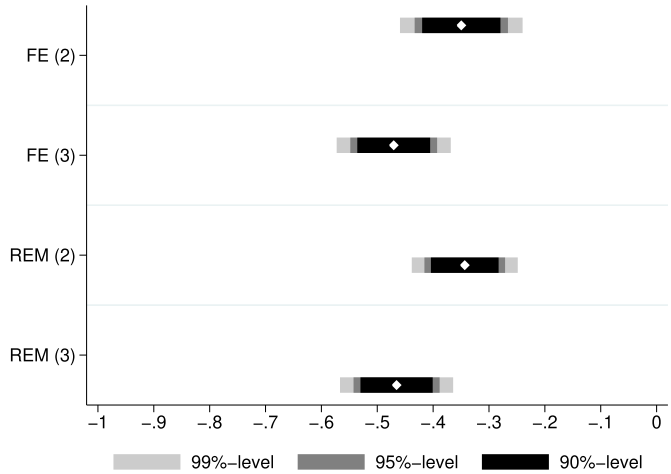

Fig. 2. Point estimates of the coefficients of the own price elasticity of electricity demand from Table 9 with 99%, 95%, and 90% confidence intervals.

Table 10
Regression models of long-run log electricity demand with only Mundlak terms.

	REM (1)	REM (2)	REM (3)
Mean of (log) average price	−0.71[a]		
	(0.03)		
Mean of (log) marginal price (own share)		−1.41[a]	
		(0.11)	
Mean of (log) marginal price (median share)			0.59[a]
			(0.18)
Mean of (log) CHF/Watt	−0.06	−0.21[a]	−0.30[a]
	(0.05)	(0.06)	(0.06)
Mean of (log) price of gas	−1.39[a]	0.47[b]	1.13[a]
	(0.07)	(0.20)	(0.09)
Mean of indicator for time-of use pricing	0.18[a]	−0.11[a]	0.24[a]
	(0.02)	(0.03)	(0.05)
Mean of (log) cooling degree days	2.78[a]	1.68[a]	−0.12
	(0.20)	(0.25)	(0.25)
Mean of (log) heating degree days	9.96[a]	5.06[a]	−1.65[b]
	(0.65)	(0.82)	(0.76)
Mean of income less than 6000 CHF/month	−0.07[b]	−0.12[a]	−0.10[a]
	(0.03)	(0.04)	(0.04)
Mean of income between 6000 and 12000 CHF/month	−0.05[c]	−0.08[b]	−0.08[b]
	(0.03)	(0.03)	(0.03)
Mean of income greater than 12000 CHF/month	−0.01	−0.04	−0.04
	(0.03)	(0.04)	(0.04)
Mean of household size	0.01	−0.01	0.02
	(0.01)	(0.01)	(0.01)
Observations	19511	18496	19511
Overall R^2	0.72	0.52	0.56

Notes: This table is an extension of the Mundlak models in Tables 3 and 9 The coefficients presented here are only those of the Mundlak terms. The dependent variable in all models is the natural logarithm of the annual household electricity consumption. The seven utilities included in all the models are AIL, ESB, EWB, EWL, IBA, IWB, and SW. Heteroscedasticity-robust standard errors are in parentheses. Significance at the 1%, 5% and 10% levels are denoted by [a], [b], and [c], respectively.

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