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Dynamic models of residential electricity demand: Evidence from Switzerland*

Nina Boogen

ETH Zürich
Zürichbergstrasse 18
8032 Zürich, Switzerland

<nboogen@ethz.ch>

Souvik Datta*

University of Glasgow
Main Building, University Avenue
Glasgow G12 8QQ, United Kingdom

<souvik.datta@alumni.ubc.ca>

Massimo Filippini

ETH Zürich and Università della Svizzera italiana
Ex Laboratorio, Office 205 (Level 2)
Via Buffi 13
6904 Lugano, Switzerland

<massimo.filippini@usi.ch>

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Abstract

We estimate the short- and long-run elasticity of electricity demand for Switzerland using a dynamic model of residential electricity consumption incorporating a correction introduced by Kiviet. We find that the short-run elasticity of residential demand for electricity in Switzerland is around -0.3 while the long-run elasticity is around -0.6. Our estimates indicate that pricing policy as a plan for energy strategy may have a moderate impact on residential customers in the short run but will have a stronger influence in the long-run. In view of the recent proposal in Switzerland to introduce a tax on electricity as part of its energy strategy plan, an increase in the price of electricity may result in a moderate decrease in electricity consumption.

Keywords: Residential electricity demand; price elasticity; partial adjustment model; dynamic demand model; panel data.
JEL Classification Codes: C23, Q41, Q48, Q58.

*Corresponding author.

1 Introduction

The Fukushima Daiichi nuclear accident on 11 March, 2011 led to worldwide discussions about the security of nuclear power plants and energy policy issues. In Germany, chancellor Angela Merkel imposed a moratorium for three months on announced extensions for existing nuclear power plants and shut down seven of its 17 power plants within days after the accident. Afterwards, the government announced that all existing power plants will be phased out by 2022. Italy has already closed down all its nuclear power plants after the Chernobyl accident. However, the government considered the possibility to build a new nuclear power plant. The referendum for this took place in June 2011 just after the Fukushima incident and a majority voted against this (Jorant, 2011). Due to the decision to phase out nuclear energy, some countries are introducing policy measures to, for example, increase the level of energy efficiency and the amount of electricity generated from renewable sources. In the short-run the possibilities for consumers are relatively limited. However, in the long run, the electricity demand may be be stabilized from policies by, for example, incentivizing consumers to switch to more energy efficient appliances.

In Switzerland, the Federal Council decided to suspend the approvals process for new nuclear reactors. It subsequently decided to make the ban on new nuclear reactors permanent. Furthermore, it was decided that the country's five existing nuclear reactors would continue producing electricity until they are gradually phased out with no replacements.[1] 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. In 2011 almost 40% of Switzerland's electricity was produced from nuclear power. The Federal Council has, therefore, developed a long-term energy strategy plan, the *Energy Strategy 2050*.

The *Energy Strategy 2050* sets out the future for Switzerland very clearly by stating that it 'is focusing on increased energy efficiency, the expansion of hydropower and use of new renewable energy, and in a second step the Council wants to replace the existing promotion system with a steering mechanism.' While the Federal Council has proposed, within the initial package of measures, mandatory efficiency goals for the utilities that sell more than 30 GWh as one way to reduce electricity consumption, switching electricity generation from nuclear to other sources would involve generating electricity from renewable sources and importing electricity from neighbouring countries. The *Energy Strategy 2050* also includes, in a later phase, a possible ecological tax reform. This will introduce an energy tax that is expected to bring about a more responsible use of resources and stabilize the consumption of electricity. In order to estimate the efficacy of an energy tax on electricity consumption it is crucial to obtain credible estimates of the responsiveness of electricity demand to changes in its price.

There is now a substantial literature that estimates the price responsiveness of residential electricity demand.[2] Studies of residential electricity demand can be at the aggregated level, e.g. at the state- or country-level. These exploit panel data (Halvorsen, 1975; Azevedo et al.,

[1]This decision is not final yet because it has not gone through the parliament yet and there is a possibility of a referendum.

[2]Heshmati (2012) provides an overview of the numerous studies. Espey and Espey (2004) use a meta-analysis to quantitatively summarize 126 previous studies,from 1971 to 2000, of residential electricity demand while Alberini et al. (2011) contains a survey of some more recent studies.

2011; Maddala et al., 1997; Liu, 2004; Carlevaro and Spierer, 1983; Spierer, 1988; Labandeira et al., 2012; Filippini, 1999; Alberini and Filippini, 2011; Blázquez et al., 2013) or, alternatively, for country studies, just the time-series nature of the data (Prosser, 1985; Bentzen and Engsted, 1993; Fatai et al., 2003; Kamerschen and Porter, 2004; Holtedahl and Joutz, 2004; Narayan and Smyth, 2005; Ziramba, 2008; Amarawickrama and Hunt, 2008; Dergiades and Tsoulfidis, 2008; Sa'ad, 2009; Fan and Hyndman, 2011).

Other studies are at the disaggregated level, e.g. using household surveys, and usually use cross-sectional data. Among early works, Houthakker (1951) looks at electricity demand using domestic two-part tariffs in 1937-38 for 42 provincial towns in Great Britain. Fisher and Kaysen (1962) study residential and industrial electricity demand in the United States. They were the first to distinguish explicitly between short-run and long-run demand. A first wave of papers on residential electricity demand was published in the 1970s, as the concerns on the limits of growth were coming up (e.g., Houthakker and Taylor (1970); Halvorsen (1975)). More recently, Reiss and White (2005) find considerable heterogeneity in the estimated price elasticities of Californian households across income and other demographic characteristics. Yoo et al. (2007) find that a plasma TV or an air conditioner significantly increases residential electricity consumption. However, the electricity demand estimated by using the average price appears to be price and income inelastic. Fell et al. (2014) use monthly data from a consumer expenditure survey collected between 2006 and 2008 and estimate the price elasticity to be 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 high price elasticity of between -0.27 and -1.4 in most countries. Compared to these cross-sectional studies, Alberini et al. (2011) find a much higher price response by residential consumers in the US ranging from -0.67 to -0.86 by using 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. Other studies that use a panel approach while utilizing disaggregated data are, e.g., Borenstein (2009) and Ito (2014).

There are many advantages of using panel data over cross-sectional data or pure time-series data. These are discussed in many standard econometric textbooks, e.g. Baltagi (2008) and Wooldridge (2002). Firstly, economic agents are usually heterogeneous and time-series and cross-section studies cannot control for this heterogeneity. This effect is called unobserved heterogeneity and 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. Thirdly, panel data have a great advantage when studying dynamic effects of adjustment that we are attempting to exploit in this paper. Aggregate time-series data may have aggregation biases that make it difficult to analyze microeconomic dynamics (Bond, 2002). Therefore, panel data allows to identify effects that are not observable in pure cross-section or time-series data.

There have been numerous studies on residential electricity demand estimation using various static and dynamic panel data approaches for different countries in the last 20 years. While most studies are on the United States (e.g. Silk and Joutz (1997); Maddala et al. (1997); Alberini and Filippini (2011)), some other countries such as Greece (Donatos and Mergos, 1991), Taiwan (Holtedahl and Joutz, 2004), Australia (Narayan and Smyth, 2005), Japan (Okajima and Okajima, 2013), and Spain (Blázquez et al., 2013; Labandeira et al., 2006) have also been studied. To obtain an overview of the huge amount of studies, Espey and Espey (2004) use a meta-analysis to quantitatively summarize 126 previous studies,from 1971 to 2000, of residential electricity demand to determine if there are factors that systematically affect estimated elasticities. In this study, price and income elasticities of residential demand for electricity from previous studies are used as the dependent variables, with data characteristics, model structure, and estimation technique as independent variables, using both least square estimation of a semi-log and maximum likelihood estimation of a gamma model. They find a mean price elasticity of -0.35 in the short-run, which increases to -0.85 in the long-run. These results show that in the short-run households are rather insensible to price changes, however in the long-run the demand clearly becomes more elastic.

Compared to the US and some other countries, studies on residential electricity demand in Switzerland are rather rare. There have been some studies using disaggregated data (Dennerlein and Flaig, 1987; Dennerlein, 1990; Zweifel et al., 1997; Boogen et al., 2014) while others have used aggregated data to estimate the electricity consumption (Carlevaro and Spierer, 1983; Spierer, 1988; Zweifel et al., 1997; Filippini, 1999, 2011). Table 1 provides an overview of the price elasticities in some selected studies.

Filippini (1999) estimates electricity demand using aggregate data for 40 Swiss cities over the period 1987 to 1990. The price elasticity is estimated to be –0.30, which shows a moderate responsiveness of electricity consumption to changes in prices. This result indicates a price-inelastic demand for electricity with lower price elasticity than those reported in previous studies. Filippini (2011) estimates the time-of-day residential demand for electricity in Switzerland. The estimated short-run own-price elasticities are –0.60 during the peak period and –0.79 during the off-peak period. The estimated long-run values are, as expected, higher than in the short-run with –0.71 during the peak period and –1.92 during the off-peak period. This indicates a high responsiveness of electricity consumption to changes in prices.

Zweifel et al. (1997) use data from around 1,300 households from different years (1989-92) and group them in three different pools depending on whether households have a single-tariff structure, a time-of-use structure and a time-of-use structure by choice. These households are customers of utilities that have either both structures or a time-of-use 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. Since the 1990s there has been no study using disaggregated data in Switzerland to estimate the price elasticity of residential electricity demand and this paper provides an update using a unique household survey.

In this paper, we estimate the short- and long-run elasticity of electricity demand which will provide a measure of how an energy tax may affect the responsiveness of electricity consumption. In addition, this will provide policy makers and utility companies with estimates needed for forecasting electricity demand and enable them to plan for generation, transmission and distribution capacities. To do this we use information from a recent survey carried out on a sample of Swiss utilities by Boogen et al. (2015). Using information on residential electricity consumption, electricity prices, household characteristics and weather factors, we estimate a dynamic model of electricity consumption. We find that the short-run elasticity of residential demand for electricity in Switzerland is inelastic at around –0.3 while the long-run elasticity, while also inelastic, is reasonably high at around –0.6.

This paper contributes to the empirical literature on short- and long-run electricity demand by estimating the respective price elasticities using a new dataset to estimate a dynamic electricity demand model. We use a correction introduced by Kiviet (1995) for the least squares dummy variable method to account for the endogeneity of the lagged dependent variable in a dynamic demand model using aggregated data. Boogen et al. (2015) use a cross-sectional household-level survey to estimate the price elasticity of residential electricity demand for Switzerland and find the long- and short-run elasticities to be from –0.4 to –0.6 and –0.4, respectively. This paper complements chapter 2 of Boogen et al. (2015) by using panel data to estimate a dynamic demand for residential electricity. As mentioned in Bond (2002), having dynamics in the underlying process is important for obtaining consistent estimates of parameters even when the coefficient on the lagged dependent variable may not be of direct interest. We also test for the equality of the estimates of the short- and long-run electricity price elasticities and find them to be statistically different. Obtaining the correct estimates of price elasticities is crucial because of their importance for bottom-up and general equilibrium models used to understand the energy system.

The structure of the paper is as follows. In the next section we describe a model of electricity demand. The variables used in our model and their sources are described in section 3. Our estimating equation and results of the estimating procedure are provided in the penultimate section. The final section has concluding remarks.

2 Dynamic Model of Electricity Demand

Household demand for electricity may be considered to be a derived demand since electricity is not consumed *per se* but to provide us with services, e.g. an electric heater providing warmth. Using the basic framework of household production theory that combines electricity and capital to provide energy services we can derive the demand for electricity.[3] As shown by some papers that estimate electricity demand using the household production function, long-run electricity demand depends on the price of electricity, the price of appliances, the price of electricity substitutes, household income, and other factors like socio-demographic and residential characteristics. On the other hand, short-run electricity demand depends on all the above factors except for the price of appliances. In this case, we substitute the price of appliances with

[3] There are numerous applications of household production for estimating the electricity demand. See, e.g., Dubin (1985), Flaig (1990), and Filippini (1999).

the actual stock of appliances due to the fact that household appliances cannot be replaced swiftly. Therefore, the demand for electricity depends on the stock of appliances owned by a household and a static model is not able to capture this long-run equilibrium.[4] The long-run equilibrium of a household's stock of appliances cannot be reached instantaneously and, in case the capital stock cannot be observed, we can use a partial adjustment model (Houthakker, 1980). This assumes that the change in actual electricity demand between two neighbouring periods, $t-1$ and t, is only some fraction, say λ, of the difference between the logarithm of actual electricity demand in time period $t-1$ and the logarithm of the long-run equilibrium electricity demand in time period t. We denote this partial adjustment model as

$$\log E_{it} - \log E_{i,t-1} = \lambda(\log E^*_{it} - \log E_{i,t-1}) \tag{1}$$

where E is the electricity demand, i denotes the utility, t is the time index and E^*_{it} denotes the long-run equilibrium demand in time period t. The value of the adjustment factor, λ, lies between 0 and 1. Equation 1 implies that given an optimum, albeit unobservable, level of electricity demand, the demand will gradually converge to the optimal level between any two time periods. We can use this model of partial adjustment to specify dynamic models of electricity demand.

Following Alberini and Filippini (2011) we can express the desired electricity use as $E^*_{it} = \alpha P_E^{\eta} \exp(X\gamma)$ where P_E is the price of electricity, η is the long-run price elasticity of electricity, X is a vector of household and socio-demographic characteristics that influence household electricity consumption. If we replace this equation in Eq.(1), rearrange it and insert a statistical error term, ε, we get

$$\log E_{it} = \lambda \log\alpha + \lambda\eta \log P_E + \lambda X\gamma + (1-\lambda)\log E_{t-1} + \varepsilon_{it}. \tag{2}$$

The short-run elasticity of electricity demand is denoted by the coefficient of the $\log P_E$ term, $\lambda\eta$, while the long-run elasticity is obtained by dividing the estimate of $\lambda\eta$ by λ. We obtain λ from the estimates in our model by subtracting the estimated coefficient of the $\log E_{i,t-1}$ term from 1.

3 Data

We use aggregate electricity consumption data at the utility level from a survey carried out by Boogen et al. (2015). Boogen et al. (2015) mailed a questionnaire to 105 utilities in Switzerland between April and November, 2013. The questionnaire was sent to the 50 largest utilities and to a random sample of 55 mid-sized utilities. Out of the 105 utilities surveyed, 30 responses were usable. These 30 utilities account for almost half of the electricity delivered to households with around 45% of residential electricity sold in 2011. Most of these utilities, around 80%, are located in the German-speaking part of Switzerland while the rest of the utilities are divided

[4] There is some debate about the short- and long-run demand estimates with Baltagi and Griffin (1984) stating that a cross-sectional analysis is an indication of the long-run estimates since the majority of households in a cross-section are well adapted to their financial circumstances and the cross-section will represent a steady-state. Therefore, the estimated elasticities will represent long-run circumstances (Thomas, 1987).

almost equally between the French-speaking and Italian-speaking parts, 10% and a little over 10%, respectively. The questionnaire included questions about the consumption of residential customers, number of customers, electricity tariffs and utility characteristics. The utilities surveyed were asked to fill in the respective data for 2006 until 2012. This means that we have a panel data set. The main advantage of using panel data is that we can control for unobserved heterogeneity of the utilities. However, we have an unbalanced panel dataset since some of the utilities were unable to provide information for the first few years. For our primary variable of interest, electricity consumption, there are 184 observations in total for the 30 utilities over 7 years.

Other sources of data are MeteoSchweiz and the Bundesamt für Statistik (BFS). Weather information on heating and cooling degree days is from MeteoSchweiz and demographic information used to calculate the household size and a measure of income are from BFS. The variables used from these two sources and the summary statistics of those variables are presented in Table 2. Apart from these variables, we also need the price electricity. We calculate this based on the information from residential electricity tariffs as

$$P_{avg} = \frac{(E_{peak} \cdot MP_{peak} + E_{off-peak} \cdot MP_{off-peak} + FF_{tou}) + (E_{single} \cdot MP_{single} + FF_{single})}{E_{total}} \tag{3}$$

where E_{peak} is the peak period consumption per customer with a TOU tariff, $E_{off-peak}$ is the off-peak period consumption per customer with a TOU tariff, E_{single} is the consumption per customer with a single tariff scheme, MP_{peak} is the marginal price of electricity in peak periods, $MP_{off-peak}$ is the marginal price of electricity in off-peak periods, MP_{peak} is the marginal price of electricity for single tariff customers, $customer_{tou}$ is the number of customers of a particular utility that have a TOU scheme, and FF is the fixed fee with subscripts tou and $single$ denoting the time-of-use and single tariff schemes, respectively, for a customer.

Using the average price, depending on the data used, can create an endogeneity problem. If disaggregated data are used, two-part and block pricing schemes mean that the average price depends on the quantity consumed by the household, and are therefore endogenous with one another. At the aggregate level, however, Shin (1985) argues that the potential for the price to be endogenous with consumption is mitigated by the presence of many different pricing levels and schemes at different locales.[5]

4 Estimation and Results

We estimate equation (2) using, first, ordinary least squares (OLS). The results are provided in Table 3 in the column labelled 'OLS'. However, OLS is unable to account for unobserved heterogeneity. The estimates are also biased and inconsistent because the inclusion of the lagged

[5]We have estimated our model using the instrumental variable method. We used the ElCom price as an instrument for the average price, similar to Boogen et al. (2014), and find that the estimates for the price variable are not statistically significant. A test for endogeneity indicated that the average price variable is not endogenous so we proceed without considering any endogeneity issues.

dependent variable violates the strict exogeneity condition since it is correlated with the error term. There are also several disadvantages of OLS over other panel data methods when we have panel data at our disposal.[6] The unobserved heterogeneity in panel data models can be incorporated by using fixed effects. In our case, we use utility-specific fixed effects to account for observations at the utility level. The results of estimating the dynamic demand model using utility-specific fixed effects (FE) are provided in the column labelled 'FE' in Table 3. However, estimating a dynamic panel data model with a lagged dependent variable in a fixed effects framework, as in the case with OLS, is not appropriate since the strict exogeneity assumption is violated. The estimated coefficients are biased and inconsistent since the lagged dependent variable is correlated with the error term. The literature mentions that the estimated coefficient for the lagged variable using OLS is biased upwards while the coefficient in a fixed effects model (or least squares dummy variable model) is biased downwards in a dynamic model.[7]

Several solutions have been proposed using the method of instrumental variables. These include proposals by Anderson and Hsiao (1982), Blundell and Bond (1998), and Arellano and Bond (1991). The general idea is to use lagged levels and, alternatively, complement them with lagged differences as valid instruments for the lagged dependent variable, i.e., they are uncorrelated with the error term. However, this can be problematic in estimation using small samples, as suggested by Baltagi (2008) and Roodman (2009). In small samples, using too many instruments leads to estimates that are biased towards OLS estimates. Also, the GMM estimators proposed by Arellano and Bond (1991) and Blundell and Bond (1998) are appropriate for samples with a large number of panel units, N, and a small number of units may lead to biased estimates.[8]

An alternative to the GMM estimators has been proposed by Kiviet (1995). This method is based on the correcting the bias of the least squares dummy variable (LSDV) method. Kiviet (1995) and Judson and Owen (1999) use Monte Carlo simulations show that in usual aggregate dynamic panel data models, with less than 20 time periods and number of units less than 50, the GMM estimator proposed by Arellano and Bond (1991) is outperformed by the estimators proposed by Anderson and Hsiao (1982) and Kiviet (1995). Since our data is relatively small, with 7 time periods and 30 utilities, we follow the method proposed by Kiviet (1995). In what follows, we refer to the corrected LSDV estimator proposed by Kiviet (1995) as the LSDVC estimator. The results of estimating the dynamic demand model using the Kiviet correction to utility-specific fixed effects are provided in the column labelled 'LSDVC' in Table 3.

The results from the OLS estimation procedure indicate that the short-run elasticity of electricity is extremely inelastic with a value of –0.12 while the long-run elasticity is extremely elastic with a value of –1.41. These are estimated by using the average price as calculated in Eq.(3). These results provide a good indication of the unsuitability of using OLS to estimate the price elasticities, both short- and long-run. Therefore, we next focus on the results using the utility-specific fixed effects.

The coefficients for the fixed effects specification indicate that the price elasticity of residen-

[6]For a description of the advantages of panel data methods over OLS please refer to a standard panel data econometrics text book, e.g. Baltagi (2008).

[7]Refer to Nickell (1981) for a discussion.

[8]We have also used GMM estimation to estimate our models. However, the results were not satisfactory.

tial electricity consumption are inelastic in the long-run but are more elastic in the short-run. The long-run elasticity is estimated to be around –0.5 while the short-run elasticity is around –0.3. The coefficients for the bias-corrected LSDV model lie between the OLS and FE estimates, as expected, with the estimates closer to the FE estimates than the OLS estimates. The long-run elasticity is around –0.6 while the short-run elasticity is –0.3. It is also reassuring to note that the elasticities when using the Kiviet correction are also statistically significant at the 5% level of significance.

Given the calculations of the short- and long-run estimates of price elasticities we need to make sure that the estimates are, indeed, different from each other. Therefore, to do this we test the equality of the short- and long-run elasticities. We report the results of these tests for our various models in Table 4. The results indicate that the short- and long-run are statistically different from each other when we consider the bias-corrected LSDV model. In all other cases, apart from the OLS model using $P_{average}$ as the average price, the estimates are not statistically different from each other. This is important because most studies do not test for the equality of the estimates and while the point estimates may appear to be different, the associated standard errors may lead to the estimates not being statistically different from each other.

The estimates for the socio-demographic and weather variables are, in general, not statistically significant. In the instances where they are statistically significant, the level of significance is mostly at the 10% level. This observation is consistent with fixed effects panel data studies that make it difficult to estimate variables that exhibit low within-variation as is typically the case for socio-demographic and weather variables. It is, however, interesting to note that when these variables are statistically significant, the signs are as expected. So, for example, increasing the heating degree days will increase per customer electricity consumption while and increase in the household size will have the same effect. All models include year fixed effects that are common to all utilities and control for overall unobserved macroeconomic factors that may affect electricity consumption.

If we compare our estimates to those of the other existing studies for Switzerland we see that, while similar to the estimates of Zweifel et al. (1997) and Filippini (1999), ours are less inelastic than those studies. Our long-run estimates are comparable to those by Spierer (1988) but not as high as the estimates reported by Carlevaro and Spierer (1983). Our short-run estimates are also lower than those reported by Carlevaro and Spierer (1983). Our estimates indicate that Swiss households are relatively price-inelastic with respective to electricity prices. Therefore, an increase in electricity prices may not get the desired effect of reducing electricity consumption by a large amount. The results suggest that a 1% increase in electricity price will cause a 0.45% reduction in electricity consumption in the long run while it will cause only a 0.23% reduction in the short run.

5 Conclusion

In this paper we estimate the residential electricity demand for households in Switzerland using a dynamic model of demand. We use an unbalanced panel dataset of 30 utilities covering 7 years from 2006 till 2012. Our results indicate that the price elasticity of electricity is inelastic, both in the short- and long-runs. We estimate the short-run price elasticity to be about –0.3 while the long-run price elasticity is about –0.6.

These estimates indicate that, from the energy stratey plan of reducing electricity consumption, pricing policy may have a moderate impact, on residential customers in the short run. However, the higher estimate of the long-run price elasticity of electricity consumption suggests that pricing policy will have a stronger influence on the long-run demand for electricity. Policy makers concerned about reducing electricity consumption may need to discuss the possibility of using a combination of policies, including pricing policy, to effectively reduce or, at least, stabilise the per customer electricity consumption in Switzerland. Our results suggest that, in view of the recent proposal to introduce a tax on electricity, an increase in the price of electricity may result in a moderate decrease in electricity consumption. The importance of *Energy Strategy 2050* emphasizes the need to have appropriate energy policies in place to mitigate the difficulties of a switch away from nuclear energy to other sources of electricity. Given the lack of recent studies in the estimation of price elasticity of electricity demand in Switzerland, especially for non-residential consumers, it is important that further research is carried out in all sectors, residential and non-residential, to obtain reliable estimates of the responsiveness of customers to price changes. Generally, this applies also for price elasticities of demand for other fuels, since the energy tax proposed within the *Energy Strategy 2050* will not only be applied on electricity but also on other sources of energy. Obtaining the correct estimates of price elasticities is crucial because of their importance for bottom-up and general equilibrium models used to understand the energy system.

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Table 1: Selected price elasticities in the literature

Author(s)	Region	Short-run	Long-run
International			
Houthakker and Taylor (1970)	USA	-0.13	-1.89
Halvorsen (1975)	USA	-1.52	
Bohi and Zimmerman (1984)	USA	-0.2	-0.7
Prosser (1985)	OECD	-0.22	-0.4
Bentzen and Engsted (1993)	Denmark	-0.14	-0.47
Maddala et al. (1997)	USA	-0.18	-0.263
Fatai et al. (2003)	New Zealand	-0.24 to -0.18;	-0.59 to -0.44
Kamerschen and Porter (2004)	USA	-0.92	
Holtedahl and Joutz (2004)	Taiwan	-0.15	
Liu (2004)	OECD	-0.17 to -0.16;	-0.52 to -0.59
Narayan and Smyth (2005)	Australia	-0.27 to -0.26;	-0.47 to -0.54
Alberini and Filippini (2011)	USA	-0.08 to -0.15	-0.43 to -0.73
Blázquez et al. (2013)	Spain	-0.07	-0.19
Switzerland			
Carlevaro and Spierer (1983)		-0.4	-1.0
Spierer (1988)			-0.5
Zweifel et al. (1997)			-0.25 to -0.4
Filippini (1999)			-0.3

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Total consumption per customer (in kWh)	4547.52	1311.02	1856.77	8418.08	182
Average price (in Rappen/kWh)	20.12	3.39	12.89	28.46	182
Degree days	3705.51	841.61	2449.22	6452.90	210
Average taxable income (in CHF/year)	30661.23	4541.94	23745.54	47150.28	210
Household size	1.86	0.55	0.76	4.24	185

Note: CHF 1 = US$ 1.05, as of 15 July, 2015.

Table 3: Dynamic models of residential electricity demand

	OLS	FE	LSDVC
L.(Log) Total consumption per customer	0.92^{a}	0.27^{c}	0.48^{a}
	(0.03)	(0.16)	(0.10)
(Log) Average price	-0.12^{b}	-0.33^{b}	-0.30^{a}
	(0.05)	(0.15)	(0.11)
(Log) Degree days	0.02	-0.50^{b}	-0.52^{c}
	(0.02)	(0.21)	(0.29)
(Log) Household size	0.02	0.15^{a}	0.13^{c}
	(0.02)	(0.04)	(0.08)
(Log) Taxable income	-0.05	0.54	0.52
	(0.04)	(0.45)	(0.51)
Intercept	1.35^{b}		
	(0.63)		
Utility fixed effects	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	152	152	152
Adjusted R^2	0.94	0.96	

Robust standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.

Table 4: Elasticity for dynamic models

	OLS	FE	LSDVC
Short-run price elasticity (SR)	-0.12^{b}	-0.33^{b}	-0.30^{a}
	(0.05)	(0.15)	(0.11)
Long-run price elasticity (LR)	-1.41^{a}	-0.46^{c}	-0.58^{b}
	(0.41)	(0.24)	(0.22)
Observations	152	152	152
Test for equality of SR vs. LR	0.00	0.31	0.05

Standard errors in parentheses.
^{a}, ^{b}, ^{c}: Significant at the 1%, 5% and 10% levels, respectively.