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Massimo Filippini

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CEPE
Zurichbergstrasse 18 (ZUE E)
CH-8032 Zurich
www.cepe.ethz.ch

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

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Massimo **Filippini**

ETH Zurich and University of Lugano, Switzerland
CEPE, Zurichbergstr. 18, 8032 Zurich, Switzerland
e-mail: mfilippini@ethz.ch
Phone: 0041 44 6320650

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Abstract

This paper presents an empirical analysis on the residential demand for electricity by time-of-day. This analysis has been performed using aggregate data at the city level for 22 Swiss cities for the period 2000 to 2006. For this purpose, we estimated two log-log demand equations for peak and off-peak electricity consumption using a static and a dynamic partial adjustment approach. These demand functions were estimated using several econometric approaches for panel data, for example LSDV, RE for static models and LSDV, and corrected LSDV estimators for dynamic models. The attempt of this empirical analysis has been to highlight some of the characteristics of the Swiss residential electricity demand. The estimated short-run own price elasticities are lower than 1, whereas in the long-run these values, as expected, are higher than 1. The estimated short run as well as long run cross-price elasticities are positive. This result shows that peak and off-peak electricity are substitutes. In this context, time differentiated prices should provide an economic incentive to customers so that they can modify consumption patterns by reducing peak demand and shifting electricity consumption from peak to off-peak periods.

JEL: D, D2, Q, Q4, Q5.
Keywords: residential electricity demand by time-of-use, panel data, partial adjustment model.

1. Introduction

The Swiss electric power industry comprises about 900 public and private sector firms that are engaged in the generation, transmission and/or distribution of electric power. There is tremendous disparity in the size of these companies and the pricing provided by them. In terms of numbers, utilities exclusively engaged in the distribution of electric power are approximately 550 in rural areas and 100 in urban areas. Most of these utilities are owned by the local municipalities and have a monopoly in the operation of the local distribution system. There is also a monopoly in the supply of electricity for small consumers with an annual consumption below 100 MWh.[1] The size of these electric utilities varies from small municipal ones selling 1 GWh power to large urban utilities selling over 2000 GWh power. The activities of these distribution electric utilities are regulated by the Federal Electricity Commission (ElCom), which supervises network utilisation tariffs as well as electricity tariffs for small consumers.[2]

Some of the about 650 electricity distribution companies have had a tradition of time-of-use tariffs. Therefore, the price of electricity consumption would depend on the time at which electricity is consumed. Generally, these companies apply simple time-of-use (TOU) differentiated tariffs with two pricing periods, a peak pricing period and an off-peak pricing period. During the weekdays, the peak pricing period usually lasts for 14 hours, from 7 AM 9 PM, and then the off-peak period begins. Further, weekend days are generally considered off-peak pricing periods.

This 'time-differentiated' pricing policy has been introduced to shift part of the demand during the on-peak period to the off-peak period and, therefore, to be able to decrease overcapacity during the off-peak period. This overcapacity usually occurs because the demand for electricity is typically cyclical. That is, it varies over time with a peak demand during the day

[1] Switzerland is a federal state composed of 26 cantons and approximately 3000 municipalities. It has a population of about 7 million persons and is characterized by a high degree of decentralization in the provision of public services. For instance, in the electric power sector each municipality has the autonomy to decide how to organize the electricity distribution on the own service territory.

[2] In 2008 the Swiss government introduced a reform of the electric power sector through the new Electricity Supply Act. The most important elements of this reform are: 1. transmission and distribution grids remain a natural monopoly; 2. introduction of a regulated third party access (TPA) system for large consumers (consumption above 100 MWh); the introduction of TPA for small consumers is scheduled for 1 January 2014. 3. Introduction of a regulation authority - the Swiss Federal Electricity Commission (ElCom).

period. An alternative instrument that can be used to shift peak demand to off-peak demand is the direct load control.

The overcapacity is further heightened because during the recent years, peak electricity consumption in Switzerland has been on the rise. The dilemma for the electricity companies is, therefore, to choose between investing in new peak capacity or to adopt some policy instruments such as load control or time-of-use rates. Time differentiated prices should aim at providing an economic incentive to customers to modify consumption patterns by reducing peak demand and shifting electricity consumption from peak to off-peak periods. In this context, information on price and cross-price elasticities of residential electricity demand by time-of-use are extremely important to assess the effectiveness of time-differentiated pricing policy.[3]

From a theoretical point of view, the application of TOU prices should aid public welfare. With the introduction of a time-differentiated pricing policy, prices are closer to marginal cost and lead to welfare. In this welfare analysis, we should also consider that the introduction of TOU prices also introduces the cost of measuring consumption by TOU, such as the cost of installation of special meters.

Several studies have been published on the empirical analysis of residential electricity demand by time of use. The majority of these studies have been published during the eighties, whereas this research topic received less attention in the past decade.[4] On the one side, we have studies undertaken by Hill et al. (1983) and Filippini (1995a) that analyze the electricity demand by time-of-use using a system of log-linear demand equations. These studies use an "ad hoc approach", that is, the models do not reflect completely the restrictions imposed by the neo-classical theory of consumer behaviour. On the other side, we have studies by Caves et al. (1980), Aubin et. al. (1995), Filippini (1995b), Baladi et. al. (1998) that analyze the allocation of electricity expenditure to peak and off-peak consumption by using conditional demand system

[3] One of the effects of reforms in the electricity sector is that spot markets for electricity have been established. As a result, the price of electricity on the wholesale market varies each hour**.** In this context, electricity distribution companies can apply a real-time pricing scheme to the customer. To be able to apply real-time pricing, special meters should be installed. In our opinion, real-time pricing is expected to become the standard for commercial and industrial customers, while time-of-use rate seems to remain an interesting solution for residential customers. Of course, with the installation of electronic devices that can be programmed to optimize electricity consumption in houses, residential customers will also be interested in real-time-pricing. Today, only few a utilities have introduced real-time pricing for residential customers.

[4]For a overview of these studies see Hawdon (1992) and, more recently, Lijesen (2007). Further, a survey of twelve experiments with peak load pricing performed in the US early in the eighties can be found in Faruqui and Malko (1983).

models consistent with the neo-classical demand theory and derived from an indirect utility or expenditure function. These studies generally assume a two-stage budgeting process on the part of consumers, that is, they present the estimation of a separable demand system for electricity. The implication of this assumption is that the elasticities reported in these studies are conditional upon allocation of total expenditure between electricity and other goods, that is, these are partial elasticities.[5]

Most of the published studies estimate electricity demand by time-of-use, using data at the household level obtained from rate experiments. During the last three decades, in countries such as US, UK and France, several demonstration projects on residential electricity consumption by time-of-use have been promoted in an attempt to better understand the effects of time-of-use pricing on residential electricity consumption.[6]

Filippini (1995a, 1995b) examined residential demand for electricity by time-of-use in Switzerland using revealed data, that is, data from companies that regularly apply time-of-use rates. In the first study, a model of two equations for peak and off-peak electricity consumption was estimated employing aggregated panel data and 40 cities. In the second study, Filippini (1995b) estimated the price and expenditure elasticities of peak and off-peak electricity consumption using a micro data set on 220 households living in 19 Swiss cities. The household version of the Almost Ideal Demand System model (AIDS) was used as a framework.

The majority of published studies estimated short-run price and cross-prices elasticities. However, price responsiveness in a time-of-use rate framework can be much greater in the long-run when customers have the possibility to react to a price increase by purchasing more efficient appliances and equipment. In the short run, residential customers can reduce usage only by forgoing consumption or by shifting consumption to off-peak periods.

The values of own, cross-prices and substitution elasticities obtained in studies on residential electricity demand by time of use are highly variable, partly because of the

[5] See Caves and Christensen (1980), Faruqui and Malkon (1983) and Mountain and Lawson (1992) for a discussion of this approach.

[6] Generally, in a rates experiment residential customers of a electric utility were selected randomly and placed on various time-of-use rates for a time horizon that ranges between two and six months. The electric utilities collected monthly data on the electricity usage of each of the selected customers during various daily time periods and thus were able to construct an interesting data set on residential electricity consumption according to time-of-use. One of the most recent experiments has been organized in 2001 in the US by Puget Sound Energy with about 240000 customers (see Faruqui and George 2002). In Europe some experiments have been organized in France (see Aubin et. al. 1995) and in UK(see Henley 1994).

differences in the model specifications such as data source and design of the experiment[7]. Moreover, elasticities reported in literature should be viewed as short run because the short duration of pricing experiments did not allow households to make a major change in use of electrical appliances that may be observed with permanent time-of-use prices.[8] Generally, we can conclude from this empirical literature that in the short term: a) the demand for electricity by time-of-use is inelastic; b) the elasticity of substitution and the cross-price elasticity are generally positive; and, c) the own-price elasticity for peak electricity demand is typically larger than the own-price elasticity for off-peak demand.[9]

The purpose of this paper is to make a contribution to the empirical literature on electricity demand by time-of-use by estimating short as well long-run price and cross-price elasticities. The novelty of this paper is the estimation of elasticities that reflect the fact that households have time to change and to buy more efficient electrical appliances. Further, this study provides electricity companies with new values of price and cross-prices elasticities and thus contributes to the rationality of the pricing decision-making process.

This paper is organized as follows- In section 2, we present the empirical specification of the electricity demand model. In section 3, we discuss data used in the analysis, while in section 4, the econometric approaches and the empirical results are presented. Some concluding remarks appear in section 5 of the paper.

2. An electricity demand by time-of-use model

Residential electricity demand by time-of-use can be specified using the basic framework of household production theory.[10] According to this theory, households purchase "goods" in the market that serve as inputs for use in production processes to produce "commodities" that appear

[7] For a recent review on price and substitution elasticities under time-of-use rates, see King and Chatterjee (2003). These authors reviewed price elasticity estimates from 35 studies. They reported an average short-run own-price elasticity of –0.3 among this group of studies, with most studies ranging between –0.1 and –0.4. For a review of older studies see Acton and Park (1984). Note that the the majority of the studies are based on data obtained from time-of-use pricing experiments.

[8] For a discussion on this issue see Faruqui and Malko (1983) and Caves et. Al. (1984).

[9] As we will discuss later, households purchase inputs (capital and electricity) to produce electricity services such as cooked food and hot water. Generally, in the short term, the capital stock is fixed. Therefore, electricity consumption in the short run may differ from the long-run equilibrium.

[10] For an application of household production theory to electricity demand analysis see Dubin (1985), Flaig (1990) and Filippini (1999).

as arguments in the household's utility function. In our specific case, a household combines electricity during the peak and off-peak periods with capital equipment to produce energy services such as heated rooms and hot water.

The production function of the energy service S can be written as:

$$S = S(E_P, E_O, CS) \tag{1}$$

where E_P is electricity consumed during peak period, E_O is electricity consumed during off-peak period and CS is the capital stock consisting of appliances. According to (1), quantities of electricity utilized at different points in time are different inputs.

Energy services S enter in the utility function of the household as an argument, along with aggregate consumption X. The utility function is influenced by household characteristics **Z** and by the weather in the area where the household resides. We denote climate and weather variables as **W**. Formally,

$$U = U(S(E_P, E_{OP}, CS), X; Z, W) \tag{2}$$

The household is then assumed to maximize its utility subject to equation (2) and the budget constraint,

$$Y - P_S \cdot S - 1 \cdot X = 0 \tag{3}$$

where Y is money income, P_S is price of the composite energy commodity, and P_X is price of composite numeraire good X. As a result, the derived demands for electricity by time-of-use and capital stock can be obtained as:

$$E_P^* = E^*(PE_P, PE_{OP}, P_{CS}, Y; Z, W) \tag{4}$$

$$E_{OP}^* = E^*(PE_P, PE_{OP}, P_{CS}, Y; Z, W) \tag{5}$$

$$CS^* = CS^*(PE_P, PE_{OP}, P_{CS}, Y; Z, W) \tag{6}$$

Equations (4)-(6) reflect the long-run equilibrium of the household. This model is static in that it assumes instantaneous adjustment in the equipment stock to variations in peak and off-peak electricity demand, so that short-run and long-run elasticities are the same.

Based on the equations (4)-(5) along with available data and using a log-log functional form, we posit the following static empirical models of electricity demand by time-of-use:[11]

$$\ln E_{Pit} = \beta_P + \beta_{PP} \ln PE_{Pit} + \beta_{POP} \ln PE_{OPit} + \beta_Y \ln Y_{it} + \beta_{HS} \ln HS_{it}$$
$$+ \beta_{HDD} \ln HDD_{it} + \beta_{CDD} \ln CDD_{it} + \varepsilon_{it} \qquad (7)$$

and

$$\ln E_{OP\,it} = \beta_{OP} + \beta_{PP} \ln PE_{Pit} + \beta_{POP} \ln PE_{OPit} + \beta_Y \ln Y_{it} + \beta_{HS} \ln HS_{it}$$
$$+ \beta_{HDD} \ln HDD_{it} + \beta_{CDD} \ln CDD_{it} + \varepsilon_{it} \qquad (8)$$

where E_{Pit} is peak aggregate electricity consumption per residential customer,
E_{OPit} is off- peak aggregate electricity consumption per residential customer, respectively.[12]
Y_{it} is income per household,
PE_{Pit} is the real price of electricity during the peak period,[13]
PE_{OPit} is the real price of electricity during the off-peak period,
HS_{it} is household size,
HDD_{it} are the heating degree days,
CDD_{it} are the cooling degree days all for country *i* in year *t* and,
ε_{it} is the disturbance term.[14]

Moreover, since electricity consumption and the regressors are in logarithms, the coefficients are directly interpretable as demand elasticities. Sometimes, it is interesting to

[11] Due to lack of data we were not able to estimate equation (6). This is a common problem that arises when using aggregate data. Moreover, cross-section data on appliance prices are not available. However, appliance prices faced by households can, apart from minor regional variations, be regarded as constant. Therefore, they may be excluded from the model without causing bias in estimation (see Halvorsen (1975)).

[12] In a preliminary analysis we also introduce in the model a dummy variable to distinguish cities offering the two-part time differentiated tariffs only to customers who use a lot of electricity during the off-peak period, for example for electric heating. As we will describe later, the econometric approach used, a LSDV approach, does not allow including in the model time invariant variables. Of course, in a LSDV approach this difference between the cities is automatically considered in the fixed effects.

[13] In Switzerland, the majority of electricity companies use a two-part tariff. This tariff consists of a fixed monthly charge and a constant price per kWh electricity consumed, that varies according to time. PE_{Pit} and PE_{OPit} in equations (7) and (8) are, therefore, the marginal prices for consumers and do not consider the fixed fee.

[14] In a preliminary analyses we also included in models (7) and (8) a time trend in order to capture the time-dependent effects of all other variables not included in the models. However, the coefficient of the income variable became insignificant. This is a usual problem that we attribute to the high correlation between these two variables.

consider that actual peak and off-peak electricity consumption may differ from the long-run equilibrium consumption because the equipment stock cannot adjust easily to the long-run equilibrium. In order to take into account this potential situation, a partial adjustment hypothesis can be used.[15] This model assumes that the change in actual demand between any two periods $t-1$ and t is only some fraction (λ) of the difference between the logarithm of actual demand in period $t-1$ and the logarithm of the long-run equilibrium demand in period t. Formally,

$$\ln y_t - \ln y_{t-1} = \lambda(\ln y_t^* - \ln y_{t-1}) \tag{9}$$

where $0<\lambda<1$.

This implies that given an optimum, but unobservable, level of peak and off-peak electricity, demand gradually converges towards the optimum level between any two time periods. Using the partial adjustment hypothesis (9) it is possible to specify dynamic demand models.

Dynamic versions of the models for residential electricity demand by time-of-use rates can be specified by adding to the explanatory variables in equations (7) and (8) the lagged electricity consumption. These dynamic models can be expressed as:

$$\ln E_{Pit} = \beta_P + \beta_{EP} \ln E_{Pit-1} + \beta_{PP} \ln PE_{Pit} + \beta_{POP} \ln PE_{OPit} + \beta_Y \ln Y_{it} + \beta_{HS} \ln HS_{it} + \beta_{HDD} \ln HDD_{it} + \beta_{CDD} \ln CDD_{it} + \varepsilon_{it} \tag{10}$$

and

$$\ln E_{OP\,it} = \beta_{OP} + \beta_{EPO} \ln E_{OPit-1} + \beta_{PP} \ln PE_{Pit} + \beta_{POP} \ln PE_{OPit} + \beta_Y \ln Y_{it} + \beta_{HS} \ln HS_{it} + \beta_{HDD} \ln HDD_{it} + \beta_{CDD} \ln CDD_{it} + \varepsilon_{it} \tag{11}$$

where E_{Pit-1} and E_{OPit-1} are peak and off-peak aggregate electricity consumption per residential customer in period t-1 respectively.

3. The Data

The data on electricity rates and demand during peak and off-peak periods covers seven annual periods from 2000 to 2006 and comes from a sample of Swiss cities. The data on rates and electricity consumption was collected via a questionnaire that was mailed to the Swiss

[15] For a discussion of the partial adjustment models in the estimation of electricity demand see Berndt (1991).

electric utilities operating in these cities. Out of the 100 questionnaires, 25 were returned and three contained incomplete information. This gave a sample of 22 cities for the analysis. The data for the other variables were taken from the annual publication of the Swiss Cities Association, the publication of the Federal finance administration and the monthly publication of the Swiss Federal Institute of Meteorology. Of course, this sample is not representative of all Swiss electricity distribution companies. However, these 22 companies can be considered representative of the mid-sized electricity distribution companies operating in Swiss urban areas. [16]

Electricity consumption per residential customer in city *i* and year *t* during peak and off-peak periods are the dependent variables (see Table 1). This is computed by dividing total residential electricity consumption in city *i* during each period by the number of residential customers in city *i*.

The majority of electric utilities in Switzerland utilize a two-part time differentiated tariff structure. Therefore, the rate schedule typically consists of a fixed monthly charge and a constant price per kWh electricity consumed that varies according to time (day/night). Generally, the price difference between peak and off-peak price is around 100%. Theoretically, the effect of the fixed fee on electricity consumption should be equal to the effect of income, but of opposite sign. To enforce this constraint, the fixed fee was subtracted directly from the income variable.[17]

Two climate variables (heating degree days and cooling degree days) are entered in the model to take into account the impact of weather on the need for space heating and cooling.

Due to lack of data, we use the per households taxable income as a proxy for per household total income (taxable and non taxable). The statistics on the taxable income in Swiss municipalities is published yearly by the Federal finance administration.

Household size, measured as population divided number of houses, is included in the model to account for the impact of number of members per household on the demand for energy services. A large household is expected to consume more electricity during the peak

[16] For instance, the two largest Swiss distribution companies operating in Geneva and Zurich has been excluded from the sample because only a relatively small share of the consumption (less than 5%) takes place during the off-peak period. This is due to the fact that only a few customers may choose TOU contracts.

[17] For an interesting discussion about the appropriate price structure to include in an electricity demand, see Taylor (1975) and Nordin (1976).

period than during the off-peak period, because larger households tend to spend more time home than small households. Table 1 gives some details on the variables employed in the analysis.

Table 1: Description of variables

Variables	1. Quartiles	2. Median	3. Quartile
Electricity consumption per customer, peak period (E_P)	1542 kWh	1928 kWh	2682 kWh
Electricity consumption per customer, off-peak period (E_{OP})	1453 kWh	1840 kWh	2336 kWh
Price during the peak period (P_{EP})	18.6 cents/kWh	20 cents/kWh	22 cents /kWh
Price during the off-peak period (P_{EO})	8.5 cents/kWh	9.5 cents/kW	10.7 cents/kWh
Household size (HS)	1.87	2.01	2.10
Taxable income per household (Y)	50953 SwF	571588 SwF	66809 SwF
Heating degree days (HDD)	3015.4	3213.70	3420.80
Cooling degree days (CDD)	120.30	159.50	265.40
Annual average fixed fee (FEE)	9 SwF	12 SwF	14 SwF
Number of customers	7483	11668	25929

4. Econometric approach and estimation results

For the estimation of electricity demand equations we have an unbalanced panel dataset. To account for unobserved heterogeneity using panel data, we can specify models with either city-specific fixed effects (LSDV) or with city-specific random effects (RE). However, the estimation of dynamic panel data models (10) and (11) using a LSDV or a RE model is not appropriate. This is because the inclusion of a lagged dependent variable in the explanatory variables violates the strict exogeneity assumption. In fact, the lagged variable is correlated with the error term and thus leads to biased and inconsistent estimates of LSDV and RE.[18] Many studies undertaken have discussed and proposed a solution to this problem using instrumental variable estimators. Anderson and Hsiao (1982) proposed a simple instrumental variable estimator. Arellano and Bond (1991) as well as Blundell and Bond (1998) have proposed two

[18] For a discussion on this issue and for a presentation of econometric models for panel data see Baltagi (2002) and Cameron and Trivedi (2010).

different estimators based on a general method of moment (GMM). The basic idea of these estimators is that lagged levels and/or additionally lagged differences are valid instruments for the lagged endogenous variable, that is, they are uncorrelated with the transformed error term. However, as discussed by Baltagi (2002) and Roodman (2009), in estimation using small samples, with an increase in the number of explanatory variables, moment conditions get close to the number of observations. In this case, the use of too many instruments tends to produce estimates that are biased toward those of the OLS.[19] Another problem of these two estimators is that their properties hold for large N, so the estimation results can be biased in panel data with a small number of cross-sectional units. An alternative approach proposed by Kiviet (1995), which is based on the correction of the bias of LSDV, has recently been used in several studies. Judson and Owen (1999) and Kviet (1995) have shown in a Monte Carlo analysis that in typical aggregate dynamic panels characterized by T less than or equal 20 and N less than or equal 50, as in our case, the Anderson-Hsiao and the Kiviet corrected LSDV (LSDVC) estimators are better than the GMM estimator proposed by Arellano and Bond (1991).

In this study we choose to estimate the static versions of the demand models (7) and (8) using a LSDV and a RE approach, whereas for the dynamic version of the demand models (10) and (11) we decided to use the following two estimators: LSDV and LSDVC. [20]

Coefficients of the static version of demand models (7) and (8) obtained using the LSDV and RE approaches are shown in Table 2. Generally, the results obtained using the two approaches are similar. In fact, the resulting Hausman test statistic yields an observed chi2 of 3.66 for the peak demand and of 7.54 for the off-peak demand. Both values are not significant at the 5% level and, therefore, we do not reject the null hypothesis of no correlation between the individual effects and the explanatory variables.

[19] From the literature it is known that in a dynamic specification the coefficient for the lagged variable obtained using OLS is biased upwards, whereas the coefficient obtained from the LSDV is biased downwards as in this case the lagged endogenous variable correlates negatively with the transformed error term. See Nickell (1981) for a discussion.

[20] In a preliminary analysis, we also employed the one-step system GMM estimator proposed by Blundell and Bond (1998). However, we found high values of the coefficients of the lagged dependent variables but did not find any plausible results in term of elasticities. This result may be due to the previously-discussed GMM small sample bias, which produces estimates that are upward biased. In fact, our data set is small (T= 6 and N= 22) and the number of instruments is close to the number of groups. For this reason, we decided not to report the results obtained with the one-step system GMM.

Table 2 Static Models. Dependent variable: log residential peak and off-peak electricity consumption per customer.

Variables	***Peak*** ***LSDV***	***Peak*** ***RE***	***Off-Peak*** ***LSDV***	***Off-Peak*** ***RE***
	Coefficients	*Coefficients*	*Coefficients*	*Coefficients*
Off-Peak electricity price ($\ln PE_{OP}$)	1.054*** (0.186)	1.141*** (0.175)	-0.948*** (0.214)	-0.901*** (0.206)
Peak price ($\ln PE_{P}$)	-0.805*** (0.168)	-0.890*** (0.156)	0.501** (0.194)	0.433** (0.184)
Income (lnY)	0.622*** (0.194)	0.497*** (0.176)	0.078 (0.223)	0.058 (0.209)
Household size (lnHS)	-0.154 (0.430)	0.021 (0.398)	-0.670 (0.495)	-0.384 (0.470)
Heating degree days (lnHDD)	0.040 (0.147)	-0.003 (0.142)	0.162 (0.170)	0.196 (0.166)
Cooling degree days (lnCDD)	-0.043*** (0.015)	-0.041*** (0.015)	-0.016 (0.017)	-0.017 (0.017)
_constant	1.972 (2.445)	3.611 (2.230)	4.522 (2.814)	4.232 (2.644)
Sample Size	133	133	133	133
R square Within	0.399	0.396	0.224	0.220
R square Between	0.197	0.250	0.004	0.025
R square Overall	0.196	0.252	0.006	0.030

*** Significant at 0.01 level. **Significant at 0.05 level. *Significant at 0.10 level. Standard errors in Parentheses.

The results of peak demand models show that the coefficients of price, income and cooling degree days' variables are significant and have the expected sign, whereas results of off-peak demand show that only the coefficients of the price variables are significant. Generally, the results are satisfactory in so far as the own-price elasticities and the cross-price elasticities, which form the primary concern of this study, are significant and carry the expected signs in all models. The estimated own price elasticities vary between -0.80 and -0.89 during the peak period

and between -0.90 and -0.95 during the off-peak period. Moreover, in all models the positive values of the cross price elasticities suggest peak and off-peak electricity to be substitutes.

The demand for electricity during the peak period is responsive to the level of income (Y), whereas during the off-peak period is not. The heating and the cooling degree day variables (HDD and CDD) have been included in the models in an effort to control for the impact of weather on electricity demand. The results show that the cooling degree days have only a relatively small negative impact on the peak electricity demand. This result may be due, in part, to the fact that summer temperatures are not extremely high in Switzerland. Therefore, there is little need for air conditioning and an increase of temperature will decrease use during the summer and in the mountains of electrical heating system. Further, the results show that heating degree days have a positive impact on off-peak electricity demand. This result may be due, in part, to the use of electricity heating appliances that, during the off-peak period, store electricity for the consumption in peak-period. Household size does not seem to influence electricity demand by time-of-use.

The coefficients of the dynamic demand models (10) and (11) obtained using the LSDV and the LSDVC approaches are shown in Table 3.

Most of the parameter estimates are statistically significant and the coefficients have the expected signs. Also, in this case the results are satisfactory in so far as the coefficients of the price variables and the coefficient of the lagged variable, coefficient used for the computation of the long-run elasticities, are significant and carry the expected signs in all models. The values of the price coefficients in both peak and off-peak electricity demand models obtained using the different estimators are relatively similar. This implies that the short-run elasticites will also be similar. As expected, the largest difference in the significant coefficients concerns the coefficient of the lagged dependent variable. Comparing the coefficient obtained with the LSDVC estimator with the value obtained with the LSDV, one can see that the bias-correction approach leads to higher coefficient estimate of the lagged variable.[21] To keep in mind that the difference in the value of the coefficient of the lagged variables observed across the estimators will, of course, influence the values of the long-run price elasticities.

[21] The analysis is performed assuming a bias correction up to order O(1/NT) and Arellano-Bond as consistent estimator in the first step. The Standard errors are calculated through bootstrapping (100 iterations).

Table 3. Dynamic Models. Dependent variable: log residential peak and off-peak electricity consumption per customer.

Variables	**LSDV Peak**	**LSDVC Peak**	**LSDV Off-Peak**	**LSDVC Off-Peak**
	Coef.	*Coef.*	*Coef.*	*Coef.*
Lagged peak electricity consumption *(*$\ln E_{P\ t-1}$*)*	*0.481**** (0.083)	*0.657**** (0.096)		
Lagged off-peak electricity consumption *(*$\ln E_{OP\ t-1}$*)*			*0.405**** (0.093)	*0.605**** (0.094)
Off-Peak electricity price ($\ln PE_{OP}$)	*0.917**** (0.192)	*0.793**** (0.216)	*-0.758**** (0.226)	*-0.652*** (0.257)
Peak price ($\ln PE_{P}$)	*-0.835**** (0.157)	*-0.778**** (0.181)	*0.407*** (0.191)	*0.363** (0.217)
Income (lnY)	*0.114* (0.173)	*0.035* (0.181)	*-0.065* (0.214)	*-0.106* (0.223)
Household size (lnHS)	*0.236* (0.411)	*0.253* (0.437)	*-0.432* (0.531)	*-0.258* (0.555)
Heating degree days (lnHDD)	*-0.058* (0.140)	*-0.063* (0.181)	*0.291* (0.178)	*0.286* (0.222)
Cooling degree days (lnCDD)	*-0.043**** (0.012)	*-0.046**** (0.014)	*-0.011* (0.016)	*-0.012* (0.016)
_cons	*4.031** (2.170)		*2.107* (2.772)	

*** Significant at 0.01 level. **Significant at 0.05 level. *Significant at 0.10 level. Standard errors in Parentheses.

Generally, the results obtained using all estimators show that socioeconomic variables such as income and household size as well the variables reflecting the weather conditions, do not seem to have an important influence on the peak and off-peak demand for electricity.

Table 4 displays estimates of the short- and long-run elasticities obtained using the LSDV and LSDVC estimation results. The estimated short-run own price elasticities vary between -0.77 and -0.84 during the peak period and between -0.75 and -0.65 during the off-peak period. In all models, the positive values of the short-run cross price elasticities suggest peak and

off-peak electricity to be substitutes. The values of cross price elasticity show that at least in the short-run, the impact of an increase of peak electricity price is relatively modest on off-peak electricity consumption. This implies that in the short run, raising peak price electricity appears not to give much incentive to customers to shift electricity consumption from peak to off-peak period.

Table 3. Short and long-run elasticities estimated using the dynamic models.

	LSDV Peak	**LSDVC Peak**	**LSDV Off-Peak**	**LSDVC Off-Peak**
Short run Own price elasticity	-0.835	-0.778	-0.758	-0.652
Short run Cross price elasticity Peak/Off-Peak and Off-Peak/Peak	0.917	0.793	0.407	0.363
Long run Own price elasticity	-1.608	-2.266	-1.273	-1.652
Long run Cross price elasticity Peak/Off-Peak and Off-Peak/Peak	1.767	2.311	0.684	0.919

The estimated short-run price elasticities are higher than the values reported in Faruqui and Malko (1983) but similar to those found in the studies by Aubin et. al. (1995) and by Filippini (1995a). However, a comparison of the results is difficult and typically inconclusive since models, data, and time periods used are not similar. Further, the majority of studies on time-of-day pricing of electricity have their empirical basis on experiments where consumers were faced with a variety of schedules and prices with, however, the guarantee that they would not have to pay more than the usual amount for their electricity consumption.[22]

[22] Note that Filippini (1995a) also reports values for the long-run elasticities. However, it has to be pointed out that these values were not obtained using a partial adjustment model, but interpreting differently the elasticities obtained using OLS and using a RE model. In fact, according to Halvorsen (1978) and Baltagi and Griffin (1984),

The estimated long-run own price elasticities vary between -1.60 and -2.26 during the peak period and between -1.27 and -1.65 during the off-peak period. Such differences are mainly due to the differences of the coefficients of the lagged demand variables obtained using different estimators. Further, in all models we found positive values of the long-run cross price elasticities. For these two models, the values of cross price elasticities (off-peak/peak) show that the impact of an increase of the peak electricity price on the off-peak electricity consumption is relatively important. This implies that in the long run, raising peak price electricity appears to have an effect on the consumption pattern.

As expected, the values of the cross-price elasticities (peak/off-peak) show that the impact of an increase in off-peak electricity price on peak electricity consumption is higher than the impact of an increase in peak electricity price on the off-peak electricity consumption. This result can be explained by the fact that the majority of electricity consumption activities in a typical household take place during the day and not during the night. To move some activities such as dish washing and laundry to late evening is more costly than the opposite.

The values of the long-run elasticities reported in Table 3 are relatively higher. We cannot exclude that this result may be due to the relatively small data set used in the empirical analysis (T= 6 and N= 22) that does not allow the bias of the LSDV results to be corrected optimally. Therefore, these values of long-run elasticities should be considered carefully.

5. Summary

In this study, we have examined the residential demand for electricity by time-of-day in Switzerland. For this purpose, a static and a dynamic version of the electricity demand by time-of-use models was estimated, while employing aggregated data that refers to seven years and 22 electric utilities operating in Swiss cities. Generally, the price difference between peak and off-peak price applied by these electricity distribution utilities is about 100%.

The empirical analysis has highlighted some of the characteristics of the Swiss residential electricity demand. The estimated own price elasticities show that the residential electricity demand during peak and off-peak periods is inelastic whereas in the long-run it

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the OLS model should yield the closest estimate of long-run response, whereas the RE model should yield short-run response. Of course, this interpretation is not straightforward and can lead to misleading results. Therefore, a direct comparison is not feasible.

becomes elastic. Moreover, the positive values of the short as well the long run cross-price elasticities suggest that peak and off-peak electricity are substitutes.

From the point of view of conserving end-use electricity, it is of great interest to know the peak and off-peak demand elasticities with respect to individual electricity prices. The fact that the cross-price elasticities are all positive has an important implication for conservation. It suggests that pricing policy, at least in the long run, can be an effective instrument for achieving electricity conservation. This also implies that time-of-use pricing in particular can contribute to more efficient utilization of existing production capacity, allowing for build up of additional capacity to be postponed. In this context, time differentiated prices should provide an economic incentive to customers to modify consumption patterns by reducing peak demand and shifting electricity consumption from peak to off-peak periods. This result supports the introduction of time-of-use rates in other Swiss electricity distribution companies; and use of this tariff structure after a reform allows prices to be closer to marginal cost.

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