Price Elasticity of Electricity Demand in France*

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Abstract

Using an unique dataset containing millions of bi-annual meter readings of electricity consumption within France from 2007 and 2015, we estimate the price elasticity of electricity expenditure of private households. We propose three different specifications for the study of price elasticities. A more canonical specification in which we regress electricity consumption on a price per kilowatt/hour; a second specification that follows Filippini (1995) and presents an Almost Identical Demand System (AIDS) model; finally an extension of the latter that allows elasticities to be season-dependent and differ between summer and winter. In all models we control for years and months fixed effects as well as weather and another set of economic variables at the department level. In our first estimation we find an elasticity of electricity consumption on price equal to -0.8, a result remarkably in line with the previous literature. In our AIDS models we also obtain results very close to the ones obtained by Filippini et Al. In particular price elasticities of -1.46 and -1.86 for peak and off-peak prices (Filippini reports -1.41 and -2.57). In our seasonal model we report elasticities for winter of -1.45 and -1.85, and for summer slightly higher in absolute value, equal to -1.61 and -2.08.

JEL Classification: Q4, Q41, C5, D12

Keywords: Electricity demand, Price elasticity

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1 Introduction

Two main advantages of our unique dataset are that 1) we cover more than 95% of private electricity consumption in metropolitan France; 2) given that we have meter readings, we observe the actual prices per kwh, and we do not need to resort to an average price given by total expenditure over total consumption (where total expenditure includes fixed costs of delivery etc...). Our data analysis is done in two steps. In our first step we use all the information available from our meter readings to create a new dataset that contains merged information from other datasets with other economic variables, mostly from INSEE and weather variables as well. In this step we exploit the nature of our original dataset using the detailed information contained especially in terms of geography (that is, INSEE and weather variables are merged based on refined geographical levels). At the same time we also create monthly data from bi-annual observations by spreading individual electricity consumption within the half year according to coefficients extracted from the official profiling system used by ERDF to compute every purchaser load curve. In our second step we select samples from our big dataset merged with other variables and with monthly data to carry on our econometric analysis with standard software.

We propose three different specifications for the study of price elasticities. The first specification, more canonical, in which we regress electricity consumption on a price per kilowatt/hour given by the actual price, for those customers that pay only one tariff, or a weighted average of different prices, for those customers who pay different prices in different times of the day. In our second specification we follow Filippini (1995) and present an Almost Identical Demand System (AIDS) model. In our last specification we extend this approach by allowing elasticities to be season-dependent and differ between summer and winter. In all models we control for years and months fixed effects as well as weather and another set of economic variables at the department level. In our first estimation we find an elasticity of electricity consumption on price equal to -0.8, a result remarkably in line with the previous literature. in our AIDS models we also obtain results very close to the ones obtained by Filippini. In particular price elasticities of -1.46 and -1.86 for peak and off-peak prices (Filippini reports -1.41 and -2.57). In our seasonal model we report elasticities for winter of -1.45 and -1.85, and for summer slightly higher in absolute value, equal to -1.61 and -2.08.

The paper proceeds as follows, in next section we present a brief summary of the relevant literature; in section 3 we detail the preliminary treatment of our big dataset; in section 4 we detail our estimation strategy and in section 5 the results; section 6 concludes.

2 Literature Review

The literature on the estimation of price elasticity of electricity demand is large. This literature can be divided in three major parts depending on the data used to estimate this elasticity, that is there are studies that use time series aggregated data, this is the most populated area of research on this issue; there are studies that use cross-section data and finally studies that use some type of panel data. Both cross-section data and panel data can be of various types depending if the observations are on single households, the most disaggregated case, or some aggregation that can varies from county levels, for example Nakajima (2010) derives his estimates from a panel data consisting of Japanese prefectures, to country level aggregate data (see for example Bernstein and Madlener (2011) for a panel of OECD countries).

2.1 Evidence from time series and long panel data

The majority of studies on the price elasticity of the demand of electricity rely on the variation of the consumption of electricity and its price in time. These studies rely either on time series or in long panel data. Long panel data are panels that usually contain aggregated data at a large level of aggregation such as countries or regions, and have observations for many years. Methodologically these studies usually employ cointegration estimation methods with autoregressive distributed lags (ARDL) as both time series of price and levels of consumptions are integrated series. The advantage of this method is that it delivers short and long run elasticities, that is, the reaction of price changes in the years immediately following the change and the reaction that will happen in a longer time span provided that the price remains relatively stable after that change. In the context of electricity demand this is a very relevant information as households, but also businesses and industrial sites, may adjust in time more than in the immediate years following the changes of price. In fact, the long run price elasticity of electricity is generally estimated to be higher than the short run elasticity. Okajima and Okajima (2013) provide a good review of the studies that employ time series or long panel data. Table 1 in their article resumes the estimates obtained for several countries, Australia, Turkey, South Africa, The United States (six studies) and Japan (two studies). Generally, the short run elasticity is quite low while the long run significantly larger, Narayan and Smyth (2005) report an elasticity for Australia of 0.26 for the short and 0.54 for the long run. Their sample spans 1959 to 1972. Halicioglu (2007) for Turkey, using data from 1968 to 2005 estimates 0.33 and 0.52 for the short and long run. Ros (2017) uses data from U.S. electricity companies in a long panel that goes from 1972 to 2009. He also finds elasticities in the same ballpark between 0.48 and 0.61, depending on the model he uses (static or dynamic). Interestingly, although not surprisingly, in the same paper Ros estimates price equations for different types of customers and finds that in those states where competition is higher electricity prices tend to be lower and that the benefit is much larger for industrial consumers than residential ones. Moreover, he also finds that total factor productivity is associated with lower prices. Dergiades and Tsoulfidis (2008) using times series for The United States from 1965 to 2006 estimates an elasticity of 1.07 in the long run. Ziramba (2008), South Africa 1978-2005, finds a completely inelastic demand of electricity with elasticities estimated at 0.02 and 0.04 in the short and long run. Nakajima and Hamori (2010) also finds a relatively inelastic demand in the The United States estimating the long run elasticity at 0.33 using long panel data aggregated at regional levels and spanning a period from 1993 to 2008. Instead, Nakajima (2010) for the period 1975-2005, using time series for Japan finds a long run elasticity of 1.13. Other studies on times series or long panel use a partial adjustment model, among those Kamerschen and Porter (2004) for The United States 1973-1998 reports elasticities of 0.13 and 1.89, Paul, Myers and Palmer (2009) also for The United States 1990-2006 reports elasticities of about 0.17 and 0.35, Alberini and Filippini (2011) still for the U.S. 1995-2007 reports 0.12 and 0.2. Finally, Okajima and Okajima (2013) for Japan report estimates of 0.4 and 0.49 for the short and long run using a sample of large panel data consisting of Japanese prefectures spanning the period of 1990-2007.

2.2 Evidence from cross section and large panel data

Studies that rely on large cross section or panel data are more rare in this literature. There are two reasons for this, one is that disaggregated data are more difficult to find, but the second important reason is that the marginal price of electricity is often the same for a large part of any sample we may have available. That is, in a cross section of households for example, we may have information on many different variables including the consumption of electricity that varies from household to household, however in most cases all households will face the exactly same price for electricity, making it difficult to estimate the price elasticity. Besides, even when the marginal price does change among households, it is usually not known in the data. Most studies therefore rely on average prices, that is they rely on data on expenditure on electricity and the implied average price paid given the actual consumption. While using average prices is mainly justified by availability of data, there is a growing consensus that this price is actually the relevant one for households to make their choices about electricity consumption, see Ito (2014) and Alberini, Gans and Velez-Lopez (2011), among others. Among the few studies, Krishnamurthy and Kristrm (2015) estimate price and income elasticities of the demand of electricity for household consumption in a panel of 11 OECD countries and find a substantial sensitivity of consumption to the average price changes, while a lower sensitivity to income. Their estimates go from -0.27 of South Korea to -1.4 of Australia, they estimate the price elasticity of France at -0.96. Alberini and Filippini (2011) focus on the demand of electricity in U.S. states and present a dynamic econometric model that delivers long and short run elasticities. Their estimates for the short run are around -0.15 and for the long run range from -0.44 to -0.73 depending on the methodology they use. Alberini and Filippini (2011) pay particular attention to two critical issues in these types of estimations, the fact that in panel models the lagged dependent variable on the right hand side of the equation is endogenous, and that electricity prices, given as averages by state, are mismeasured. They use Kiviet Least Square Dummy Variables (LSDV) and Blundell-Bond procedures to correct for the first issue, and IV for the second. Filippini (2011) conducts a similar analysis as in Alberini and Filippini (2011), but with Switzerland data and he identifies off-peak and peak elasticities. He also finds that the consumers substitute between off-peak and peak times according to the price schedules. All the studies above, and the many cited in those papers, assume that households are "price-takers" in the sense that they can adjust their consumption for a given price of electricity. Reiss and White (2005) develop a model that takes into account "endogenous sorting along a nonlinear price schedule", to take into account the possibility that different households choose different price schedules offered by local utilities. They "estimate a model of household electricity demand that can be used to evaluate alternative tariff designs. The model focuses on the heterogeneity in households demand elasticities, their relation to appliance holdings and other household characteristics, and how they inform household consumption responses to complex (nonlinear) price schedule changes." Reiss and White (2005) find that their estimated average elasticities are slightly higher in magnitude that what would be obtained with more traditional estimation methods.

3 Available Data and Preliminary Treatment

Given the nature of the data available to us, we conduct our analysis in two steps. In the first step we work with our original data set provided by ERDF to generate monthly observation and to make the data set consistent for the merging with other variables obtained from INSEE. In the second step we extract a sub-sample from our original data set, we merge other variables at a refined geographical level and we carry on our econometric analysis with standard softwares. Our data is collected from meter readings of more than 95% of electricity private customers in metropolitan France. The readings are done roughly every six months and, therefore, record the electricity consumption between these two dates. Our starting point is an amount of electricity effectively consumed in a certain time span by a meter, usually referring to a household. Electricity customers are of three types depending on the contract they subscribe, households who subscribe a single price per Kwh during the whole day are the BASE customers, customers who subscribe two different prices for peak (day) and off-peak (night) are called P/OP. The third category of customers are called TEMPO and subscribe a contract with six different prices for Kwh that combine the P/OP option with a series of three types of days, color coded with RED, WHITE and BLUE, from more to least expensive. Customers also differ in terms of power subscription, which defines the amount of Kw can be consumed at any point in time, the higher is the amount subscribed the higher is the fixed cost associated to the contract. The BASE and P/OP options do not have constraints in terms of minimum power subscription (3 Kw is in fact the minimum for a contract), while the subscription of a TEMPO contract requires a minimum of power subscription. For this reason TEMPO customers are generally expected to have higher consumption of electricity, while they represent a small sample of the whole electricity market. For each meter our data set records an ID, which identifies the site (or meter), the date at which the measurement starts and the date at which ends. Therefore, readings are recorded for each segment of consumption (peak, off-peak and for each type of day for TEMPO customers), and the consumption in Kwh per type is also recorded. Our data set contains 36,390,648 meters recorded over a period of 8 years from 2007 for more than 800 millions observations. Another set of observations per meter gives the possibility to identify the contract, including the power subscribed, and the prices per Kwh for each segment of consumption. Interestingly, segments of consumption differ within different locations in France, therefore our data also reports the exact times for the segments for each meter.

A major issue we face with our data is given by the fact that the dates at which meters are recorded vary with the meters, hence, even though all meters are recorded every six months and the electricity consumption is taken over those months, the time at which meters are read is different depending on the meter and, as such, those readings cannot be immediately compared across different meters. We therefore need to make our consumption observations comparable across meters before we can carry out our econometrics analysis of the data . The following subsection describes our methodology that makes the observations comparable.

3.1 Harmonization of Electricity Load Observations

The harmonization of load observations is done using coefficients provided directly by RTE and ENEDIS, the network operators for electricity in France. These coefficients in turns are calculated using a representative panel of electricity customers for which electricity is measured every 10 minutes. In practice, the coefficients serve to extrapolate the behavior in terms of electricity use observed from the panel to the entire universe of meters observed. The panel is rich in terms of frequency of observations, but, given the sample nature of the data, not as rich in terms of other covariates such as geographical variables. The coefficients are then calculated per profile, that is if the meter has a contract that is BASE, P/OP or TEMPO. The coefficients for each profile are further enrich with weather variables in order to take into account the possible change in consumption due to colder or warmer days or hours of the day.

Therefore, let's define the coefficients that take into account climate and profiles $C(j, w, d, h, t)$, where j stands for profile, w, d, h and t for week, day, hour (actually measured in slots of half an hour) and a classification of time, we can, given the annual average consumption of a profile, infer an semi-hourly consumption by simply multiplying the annual average to the coefficient. Let's call the semi-hourly consumption $P(j, w, d, h)$ we have,

$$PM(j, w, d, h) = PM_Y(j) \cdot C(j, w, d, h, t)$$

where $PM_Y(j)$ is the average consumption in a given year, which we don't know, and weather is a function of the particular day and hour of the year. The consumption of electricity in Kwh actually recorded for any period of time P, can be written as follows,

$$Q(j, P) = \frac{1}{2} \sum_{i \in P} PM(j, i) = PM_Y(j) \cdot C(j, i)$$

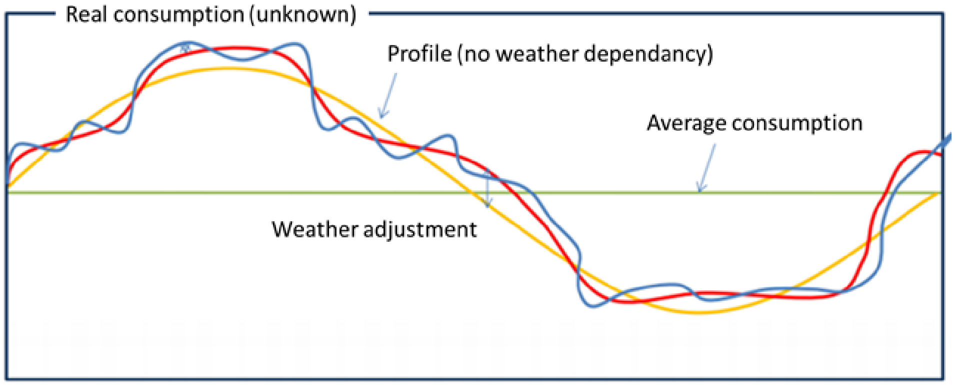
where the index $i = (w, d, h)$ contains all the information on time and weather and has a frequency of half an hour (reason why the sum is divided by 2 to report hourly consumption of Kw). From here we can derive the yearly average consumption given by,

$$PM_Y(j) = \frac{2Q(j, P)}{\sum_{i \in P} C(j, i)}.$$

Figure 1 illustrate the procedure with an example. The green flat line is the observed average consumption within the observation period, i.e. six months. The red line is the actual unknown consumption. The yellow smooth line is the imputed consumption that derives from the application on the coefficients associated to the profile, while the blue line takes into account also the weather. The blue line is assumed to be the best predictor of real consumption at any point in time.

Once we know the average consumption per year and the coefficients $C(j, i)$ we can calculate the consumption per any half an hour for each meter in our data set and aggregate as needed to find daily, weekly, monthly or semi-annual consumptions. As a result, we end up with a

Figure 1: Example of an imputed profile



data set in which we have recorded the meter identifier; a variable the identifies if consumption is during peak/off-peak hours; the calendar month and total consumption during the month. For the period we cover we have about two billions observations.

3.2 Extracting a Sub Sample for the Analysis

Once we have harmonized the observations so that one period observation means the same period for all meters, given the very large number of observations we have we extract from our data set a random sample of 1% of all observations. Given the refined geographical indication of the meters, we merge to our sample a series of other economic variables such as the consumers price index (CPI), and indicators of the economic activity of the geographical locations (among them the share of working individuals, the average education etc...).

One first thing to notice is the important difference between the TEMPO and other contracts. While for the one basic price and the two-price contracts prices change deterministically with time and only within the day, with TEMPO contracts prices can change also by day and, most importantly, the price applied to each day is chosen by the electricity provider with a few hours of advance notice. Indeed, the electricity providers strategically set higher prices in those days when they expect the demand of electricity to be higher (for example cold winter days). This induces a strong endogeneity to the price for the TEMPO customers that, as we argue below, is not present for other customers. For this reason, and knowing that they account for a small portion of the overall market, we exclude TEMPO customers from our analysis.

4 Analysis

We propose three different specifications for the study of price elasticities. The first specification, more canonical, in which we regress electricity consumption on a price per kilowatt/hour given by the actual price, for those customers that pay only one tariff, or a weighted average of different prices, for those customers who pay different prices in different times of the day. In our second specification we follow Filippini (1995) and present an Almost Identical Demand System (AIDS) model. In our last specification we extend this approach by allowing elasticities to be season-dependent and differ between summer and winter. In all models we control for years and months fixed effects as well as weather and another set of economic variables at the department level that includes the number of days per month in which the temperature exceeds 15 degrees, a threshold of so called comfort under which house heating is probably required; the actual number of days in a month; the share of homes that are reported as main residences; the share of dwelling built before 1990; the share of houses over all dwellings. All variables that help us control for factors that can affect electricity consumption and that, especially in its time dimension, could also be correlated with the price of electricity. We also add variable such as the average age of population; the share of the population in the labor force and the share of college educated.

4.1 Price Setting in France

Estimating the demand elasticity of any good or service is a difficult task as price and quantity are generally equilibrium objects determined simultaneously. As such, in a simple regression model such the one we carry on in this paper, a problem of endogeneity arises that could bias the estimates. That is why most often other models such as instrumental variable are used to correct for this potential bias. In our case, however, we have good reasons to believe that the prices of electricity in the French market have a high degree of exogeneity that derives from the rules the French Government imposes to the price setting of the main company that delivers electricity.

Electricity in France is mainly produced by EDF, a publicly participated company that since 1946 has been charged by the Government of France to produce and distribute electricity in a regime of quasi-monopoly (i..e it excludes some very large corporations), as a public service. This regime has been slightly changed in 2007 with the introduction of a competitive market for electricity provision and the distinction between provision and distribution of electricity. The company ERDF, later ENEDIS, was created and kept fully in a monopoly regime under the government for the distribution of electricity, while together with EDF, still largely participated and controlled by the government, other companies were allowed to provide energy to the final customer, by using ENEDIS for distribution. However, the competition has been asymmetric in that EDF has kept a regime of price setting entirely decided by the government while other other companies were allowed to offer different schedules. Those companies though, still face the same prices of EDF at source hence their competition is mainly exercised by offering different schedules between fixed price and peak/off-peak tariffs. The price setting of EDF is quite transparent: the variable part reflects the marginal cost of producing electricity, while the fixed cost is calculated to cover the investment part needed to keep the capacity to produce and deliver electricity. Therefore, we are quite confident that the EDF pricing schedules can be taken exogenously in our analysis, while we would be less confident for the part of customers that rely on the "market" pricing that compete with EDF. Fortunately, while our data cover a time span from 2007 to 2015, that is after the opening to competition, up to 2015 only a small portion of the French customers have chosen to rely on competition. In 2014 the share of those that chose market prices was only 6.7%, while in 2017 rose to 13%. That means that most of our observations have prices set by EDF.[1]

4.2 One-Price Model

Our preferred specification for the estimation of the elasticity with respect to its own price is a fixed effects regression model in which we control for time variables, i.e. years and months (for seasonality effects as long as year effects). Price and consumption are measured at the meter level. We also include economic and demographic variables by location that we think may affect the relationship between the consumption and the price of electricity. These variables are collected at the department level and associated to the meters depending on their locations. The average price for the basic customer is given by the variable component of the actual price

[1] See http://www.cre.fr/marches/marche-de-detail/marche-de-l-electricite for a full description.

paid. For customers who pay two variable prices for peak and off-peak consumption, the average is taken weighting by the share of total consumption at that price. That is, let C_i be the consumption for price P_i, and let C be total consumption such that

$$C = \sum_{i}^{n} C_i$$

with $n = 2$, then we define the average variable price as

$$P = \sum_{i}^{n} W_i P_i$$

with

$$W_i = \frac{C_i}{C}.$$

Moreover, all prices are expressed in constant 2005 euros as we deflate them using the CPI index.

4.3 Two-Price Model

Another set of models we estimated, to retain interesting information on the behaviour of households in terms of reacting to the difference in price within different time segments of the day are the Almost Identical Demand System (AIDS) class of models. We follow Filippini (1995) and replicate its study done for Swiss customers using our much more comprehensive data set.[2] In order to make our estimates comparable with those in Filippini, we build our dependent variable to represent the share of the electricity expenditure during peak and off-peak hours. That is, rather than raw consumption of electricity, we calculate the total variable expenditure in electricity and then the share during the two time segment of the day as follows,

$$m = \sum_{i}^{2} C_i P_i$$

$$w_i = \frac{C_i P_i}{m}$$

where m is the total variable expenditure in electricity.

[2]Naturally we restrict our sample to only those customers who pay two prices and exclude those who pay only one price as well as the TEMPO customers.

As independent variables we use the log of the prices of the two time segments and the log of total expenditure in real terms for electricity. We repeated the estimation for the whole sample and also distinguishing winter and summer seasons. This model estimates partial elasticities of the demand of electricity in the two time segments conditional on a total consumption of electricity kept constant. To this extent it gives us additional information on how customers that face two different prices, allocate their consumption in one or the other segment when the relative price changes. These models do not tell us the overall change in consumption of electricity with respect to its price, as the one-price model does.

The equations we estimated have the following form,

$$w_i = \mu_i + \sum_j \gamma_{ij} \log P_{ij} + \beta_p \log \frac{m}{P} + X'\theta \tag{1}$$

where, $i = p, o$, $j = p, o$ for peak and off-peak and P is the Stone index of the price of electricity:

$$P = \sum_j w_j \log P_j \tag{2}$$

and finally $X'\theta$ is a set of demand shifters that can affect the demand of electricity.

In addition, homogeneity and symmetry are imposed to the estimation by restricting the parameters such that,

$\sum_i \gamma_{ij} = 0$ and $\gamma_{ij} = \gamma_{ji}$

Own price and cross elasticities can be computed as follows,

$$\hat{\epsilon}_{ii} = -1 + \frac{\hat{\gamma}_{ii}}{\hat{w}_i} - \hat{\beta}_m \tag{3}$$

$$\hat{\epsilon}_{ij} = \frac{\hat{\gamma}_{ij}}{\hat{w}_i} - \hat{\beta}_m \frac{\hat{w}_j}{\hat{w}_i} \tag{4}$$

where the share of the electricity expenditures can be estimated by the average over the sample.

Finally, the elasticity of substitution is obtained by,

$$\hat{\sigma}_{ij} = 1 + \frac{\hat{\gamma}_{ij}}{\hat{w}_i \hat{w}_j} \tag{5}$$

5 Results

Tables 1 report the results relative to the one-price model. The elasticity of the demand of electricity with respect to its own price is about -0.8. Our result seems to be in line with estimates obtained in other studies especially for European countries. For example Krishnamurthy and Kristrm (2015) find, using very different data, an elasticity for France of -0.96, quite close to our result. To notice also that the correlation between the consumption of electricity and its fixed price is positive. This result is induced by the structure of the contracts that make pay more those households that need larger power absorbtion, and, therefore, will inevitably consume more. For this reason, and being impossible to disentangle this effect from the elasticity effect of price on demand, we include the fixed price to control for power subscription but do not interpret this coefficient as an effect of price on demand. This also suggests that using the average price to estimate the elasticity of electricity implies a downward bias as the fix component of the average price will tend to counter the negative relationship between the price per Kw and the consumption of electricity.

In Table 2 we reproduce the previous model but for seasonal consumption. That is, we split the same for winter and summer consumption and look at the elasticity during those two different seasons. As we can observe from the Table, the elasticity in winter results higher than in summer. To some extent this may seem counter intuitive as during winter months customers consume more electricity needing more electricity for heating. However, heating electricity can be derived by different sources such as fuel, gas, etc... and, in fact, the market offers more choices for heating needs than for other types of energy consumption. This probably explains why during winter customers are more sensitive to the price of electricity. During summer months, instead, the demand of energy is generally lower but often more difficult to be satisfied by alternative sources of energy.

5.1 Almost Identical Demand System

As our data records actual electricity consumption and actual variable prices directly related to peak and off-peak consumption, we can replicate, using our large and representative dataset, the AIDS model used in Filippini et Al. (1995) and extend it to a seasonal model as well. The

Table 1: One-Price Model

Variable	Parameter Estimate	Standard Error
Intercept	0.7769	0.0117
$\log P$	-0.7997	0.0031
$\log P_{fixed}$	1.1044	0.0006
TR	0.0002	0.0000
Nj	-0.0035	0.0001
Time Dummies	yes	
System R-Square	0.2989	

Dependent Variable: Consumption of electricity. For more details on the control variables see Table A.1

Table 2: One-Price Seasonal Model

	Winter		Summer	
Variable	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Intercept	-0.7053	0.0225	0.9075	0.0150
$\log P$	-1.1611	0.0050	-0.6358	0.0039
$\log P_{fixed}$	1.2279	0.0009	1.0089	0.0007
TR	0.0002	0.0000	0.0003	0.0000
Time Dummies	yes		yes	
System R-Square	0.3054		0.2630	

Dependent Variable: Consumption of electricity. For more details on the control variables see Table A.2

AIDS model gives us additional information on how customers shift their consumption from one time segment to another when the relative price of consumption in those segments changes, and, as such, adds precious information on the behavior of customers. Table 3 reports the results from the general regression model, while Table 4 reports the implied elasticities. Our results are immediately comparable with the estimates of Filippini as, except for the variables we control for, the methodology is exactly the same. We therefore include the estimates from his study in column 2. Our estimates are remarkable close to the estimates of Filippini even though our data are for a different country and for a different period. Especially the price elasticity for peak hours is -1.47 in our study compared to -1.41 in Filippini, therefore basically the same. Our off-peak elasticity results instead lower, but it is still higher than the elasticity for peak hour. This result is quite expected as off-peak are low demand hours and customers decide to shift from peak to off-peak to take advantage of lower prices. Overall, the elasticity of substitution tells us that for our estimates the two segments are slightly less substitutable than in Filippini, but the substitution is still substantial.[3] Table 5 shows the results for the seasonal model, i.e. the estimates are taken only for winter or for summer months. In this case we can notice that the estimates are not very different in the two seasons, however we see slightly higher elasticities during summer compare to winter. The one-price model told us that the overall elasticity of the demand of electricity with respect to the one average variable price is higher in winter than in summer, however, the two-price model tells us that conditional on reacting more strongly to the average price in winter, the allocation between peak and off-peak during this time is more rigid.

6 Conclusion

In this paper, we use data of electricity consumption within France from 2007 and 2015 and estimate the price elasticity of electricity expenditure of private households. We propose three different specifications for the study of price elasticity. We first regress electricity consumption on a price per kilowatt/hour and find an elasticity of electricity consumption on price equal to -0.8, a result remarkably in line with the previous literature. In our second specification we follow Filippini (1995) and estimate an Almost Identical Demand System (AIDS) model obtaining results very similar results in spite of the different data we use. In particular price elasticities of -1.46 and -1.86 for peak and off-peak prices (Filippini reports -1.41 and -2.57). Finally, we extend the AIDS model allowing elasticities to be season-dependent and differ

[3]The difference might be due to the fact that the share of electric heating in the total of electricity consumption in Switzerland is lower (in %) than in France while the consumption component of electricity due to heating is though to be the least elastic among households.

Table 3: Two-Price AIDS Model

Variable	Parameter Estimate	Standard Error
Intercept	0.1443	0.0009
$\log P_p$	-0.3025	0.0002
$\log P_o$	0.3025	0.0002
$\log \frac{m}{P}$	-0.0087	0.0001
$\log P_{fixed}$	-0.0328	0.0001
TR	-0.0001	0.0000
Nj	0.0031	0.0000
Time Dummies	yes	
System R-Square	0.2974	
N. Obs .	16,133,468	

Dependent Variable: Share of consumption of electricity during peak hours. The SYSLIN Procedure Iterative Seemingly Unrelated Regression Estimation.

Table 4: Price Elasticity of Electricity Demand - ERDF (Two Price Model)

	This Study	Filippini 1995a
Price elasticity, peak	-1.47	- 1.41
Price elasticity, off-peak	-1.87	- 2.57
Cross-price elasticity peak/off-peak	0.46	0.41
Cross-price elasticity, off-peak/peak	0.85	1.57
Elasticity of substitution	2.32	2.98

Table 5: Price Elasticity of Electricity Demand - ERDF (Two Price Seasonal Model)

	This Study		Filippini 1995a
	Winter	Summer	
Price elasticity, peak	-1.42	-1.63	- 1.41
Price elasticity, off-peak	-1.80	-2.11	- 2.57
Cross-price elasticity peak/off-peak	0.41	0.61	0.41
Cross-price elasticity, off-peak/peak	0.78	1.08	1.57
Elasticity of substitution	2.20	2.72	2.98

between summer and winter. In our seasonal model we report elasticities for winter of -1.45 and -1.85, and for summer slightly higher in absolute value, equal to -1.61 and -2.08. In all models we control for years and months fixed effects as well as weather and another set of economic variables at the department level.

7 Appendix

This appendix contains more details of the regressions presented in the text.

Table A.1: Full Regression for Table 1

Variable	Par. Est.	Std Error
Intercept	0.7681	0.0118
lp	-0.7992	0.0031
lfix	1.1044	0.0006
TR	0.0002	0.0001
Nj	-0.0035	0.0001
Txactifs	0.4117	0.0066
AgeMoyenPop	-0.0083	0.0001
TXresPrinc	1.2524	0.0033
TxMaison	0.4005	0.0013
TxNonScolariseDiplomesSupBac	0.0968	0.0032
TxResConbstrAv1990	-0.5468	0.0106
OilPrice	0.0002	0.0000
Time Fixed Effects	YES	
Number of Obs.	19,768,361	
R-Square	0.2989	

Dependent variable lc: (natural) log of consumption; lp: (natural) log of average variable price; lfix: (natural) log of fix price; TR: number of days in which the temperature is below 15 degree C; Nj: number of days recorder in the month; Txactifs: Share of people in the labor force; AgeMoyenPop: Average age of population; TXresPrinc: Share of home as main residence; TxMaison: Share of houses over all dwellings; TxNonScolariseDiplomesSupBac: Share of College Educated; TxResConbstrAv1990: Share of Dwelling built before 1990.

Table A.2: Full Regression for Table 2

	Winter		Summer	
Variable	Par. Est.	Std Error	Par. Est.	Std Error
Intercept	-0.7054	0.0225	0.9075	0.0150
lp	-1.1611	0.0050	-0.6358	0.0040
lfix	1.2279	0.0009	1.0089	0.0007
TR	0.0003	0.0000	0.0003	0.0000
Nj	0.0000	0.0005	0.0021	0.0002
Txactifs	0.7482	0.0105	0.1825	0.0085
AgeMoyenPop	-0.0086	0.0001	-0.0081	0.0001
TXresPrinc	1.3117	0.0053	1.2192	0.0043
TxMaison	0.4476	0.0021	0.3686	0.0017
TxNonScolariseDiplomesSupBac	0.0299	0.0051	0.1396	0.0042
TxResConbstrAv1990	-0.6773	0.0168	-0.4890	0.0136
OilPrice	0.0002	0.0000	-0.0002	0.0001
Time Fixed Effects	YES		YES	
Number of Obs.	8,455,612		11,312,749	
R-Square	0.3054		0.2630	

Dependent variable lc: (natural) log of consumption; lp: (natural) log of average variable price; lfix: (natural) log of fix price; TR: number of days in which the temperature is below 15 degree C; Nj: number of days recorder in the month; Txactifs: Share of people in the labor force; AgeMoyenPop: Average age of population; TXresPrinc: Share of home as main residence; TxMaison: Share of houses over all dwellings; TxNonScolariseDiplomesSupBac: Share of College Educated; TxResConbstrAv1990: Share of Dwelling built before 1990.

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