Price Elasticity of Electricity Demand in France

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Abstract – Competition and climate becoming more important for electricity production and consumption, market operators are increasingly interested in reliable forecasts of electricity prices and consumption for planning their investments and regulating policies. Key for good forecasts is understanding the consumers' reaction to price changes, synthesized by the concept of elasticity. Using a unique dataset of millions of bi-annual meter readings of electricity consumption in France from 2007 to 2015, we estimate the price elasticity of electricity expenditure of private households. We propose three specifications: a canonical one that regresses electricity consumption on a price per kilowatt/hour, where we find an elasticity equal to -0.8, a result remarkably in line and corroborating previous literature; a specification that follows Filippini's (1995) model of an Almost Ideal Demand System (AIDS), in which we substantially replicate his results; and finally, an extension of the latter that allows elasticities to be season-dependent that shows the demand of electricity being more elastic in summer.

JEL Classification: Q4, Q41, C5, D12
Keywords: electricity demand, price elasticity

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We thank Électricité Réseau De France (now Enedis) for sharing and letting us use their data, and more particularly Mathieu Bordigoni, Jean-Baptiste Galland and Laurent Gilotte for their help.

Received 19 July 2017, accepted after revisions 20 January 2019.

Citation: Auray, S., Caponi, V. & Ravel, B. (2019). Price Elasticity of Electricity Demand in France. *Economie et Statistique / Economics and Statistics*, 513, 91–103. https://doi.org/10.24187/ecostat.2019.513.2002

Electricity is generally considered as a utility and, especially because of historical reasons, its price is set mostly on a production cost basis. Nowadays, where competition and climate changes have become more and more important, it is increasingly useful for regulators and operators in the electricity market to analyse the reaction of consumers to price changes. In particular, network operators (Transmission System Operators and distributors) need to plan their investments considering their forecast of prices changes and the related reaction of the consumers. We use a large set of data on the French electricity market to estimate the elasticity of electricity consumption. Our large and unique dataset allows us to replicate some of the results already acquired in the literature of an elasticity for France close to -1, corroborating this finding. We also replicate the results found in Filippini (1995) for a two-tariff model using data on a different country and we go further using the same modeling strategy introducing a seasonal model. Our main contribution is twofold: on the one hand we corroborate the results found in the previous literature with a dataset that is massively representative, on the other hand, given the richness of our data we further split the sample to take seasonal differences in the consumption behaviour into account.

Two main advantages of our unique dataset are that: 1) it covers more than 95% of private electricity consumption in metropolitan France and 2) being based on meter readings, we observe the actual prices per kWh so that 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 made in two steps. In the first step, we use all the information available from our meter readings to create a new dataset merging economic and geographical information from other datasets, mostly from Insee, and also including weather variables, at more detailed geographical level. 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 the operator of the electricity network in France (ERDF, now Enedis) to compute every customer load curve. In the second step we select samples from our big dataset merged with other variables and with monthly data to carry on our econometric 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 customers who pay different prices at different times of the day. In our second specification we follow Filippini (1995) and present an Almost Ideal 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 a set of economic variables at the department level. In our first estimation we find a price elasticity of electricity consumption 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 the first section we present a brief review of the relevant literature; in section 2 we detail the preliminary treatment of our main dataset; in section 3 we detail our estimation strategy and in section 4 we present the results.

1. Literature Review

The literature on the estimation of price elasticity of electricity demand is vast. This literature can be divided into three major strands depending on the data used: 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 whether the observations are single households, the most disaggregated case, or some aggregation that can differ from county levels. For example Nakajima (2010) derives his estimates from panel data of Japanese prefectures, to country level aggregate data (see also Bernstein & Madlener, 2011, for a panel of OECD countries).

1.1. Evidence from Time Series and Long Panel Data

Most studies on the price elasticity of the demand of electricity rely on the variation of the consumption of electricity and its price over time. These studies rely either on time series or on long panel data. Long panel data are panels that usually contain aggregated data at a high level of aggregation such as countries or regions and have observations for many years. Methodologically these studies usually employ cointegration estimation methods with auto-regressive 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 to price changes in the years immediately following the change as well as the reaction that will happen in a longer time span provided that the price remains relatively stable. In the context of electricity demand this is a very relevant information as households, but also businesses and industrial sites, may choose to delay or span their adjustment in time. In fact, the long run price elasticity of electricity is generally estimated to be higher than the short run elasticity. Okajima & Okajima (2013) provide a good review of the studies that employ time series or long panel data and present 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 elasticity is significantly larger; Narayan & 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 elasticities. 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 electricity prices tend to be lower in those states where competition is higher 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 & Tsoulfidis (2008) using times series for the United States from 1965 to 2006 estimate an elasticity of 1.07 in the long run. Ziramba (2008), for South Africa 1978-2005, finds a completely inelastic price elasticity demand with elasticities estimated at 0.02 and 0.04 in the short and long run. Nakajima & Hamori (2010b) also find 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 based on times series or long panel data use a partial adjustment model, among those Kamerschen & Porter (2004) for the United States 1973-1998 report elasticities of 0.13 and 1.89, Paul *et al.* (2009) also for the United States 1990-2006 report elasticities of about 0.17 and 0.35, Alberini & Filippini (2011) still for the U.S. 1995-2007 report 0.12 and 0.2. Finally, Okajima & 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.

1.2. 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 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, but 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 across households, it is usually not known in the data. Most studies therefore rely on average prices that is, 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 consensus that the marginal price is the relevant one for households to make their choices about electricity consumption, see Ito (2014) and Alberini *et al.* (2011), among others. Among the few studies using panel data, Krishnamurthy & Kriström (2015) estimate price and income elasticities of the demand of electricity for household consumption with a panel of eleven OECD countries and find a substantial sensitivity of consumption to changes in average price and a lower sensitivity to changes in income. Price-elasticity goes from -0.27 for South Korea to -1.4 for Australia, they estimate the price elasticity for France at

-0.96. Alberini & 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 & Filippini 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 & 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 & 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 & White (2005) find that their estimated average elasticities are slightly higher than what would be obtained with more traditional estimation methods.

2. 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 the original data set, we merge other variables at a refined geographical level to carry on our econometric analysis. The dataset includes meter readings of more than 95% of 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 at 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 per 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 dataset 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 eight years from 2007 for more than 800 million 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 between different locations in France, therefore our data also reports the exact times for the segments for each meter.

A major issue with these data is the fact that the dates at which meters are recorded vary with the meters, even though all meters are recorded every six months. This asynchronous recording makes it impossible to compare readings across different meters. We therefore need to make our consumption observations comparable across meters before we can carry out our econometric analysis. The following subsection describes our methodology to make the observations comparable.

2.1. Harmonization of Electricity Load Observations

The harmonization of electricity load observations is done using coefficients provided directly by RTE and Enedis, the electricity network operators in France. These coefficients in turn are calculated using a representative panel of electricity customers for which electricity is measured every ten minutes. In practice, the coefficients serve to extrapolate the electricity usage behaviour 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 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:

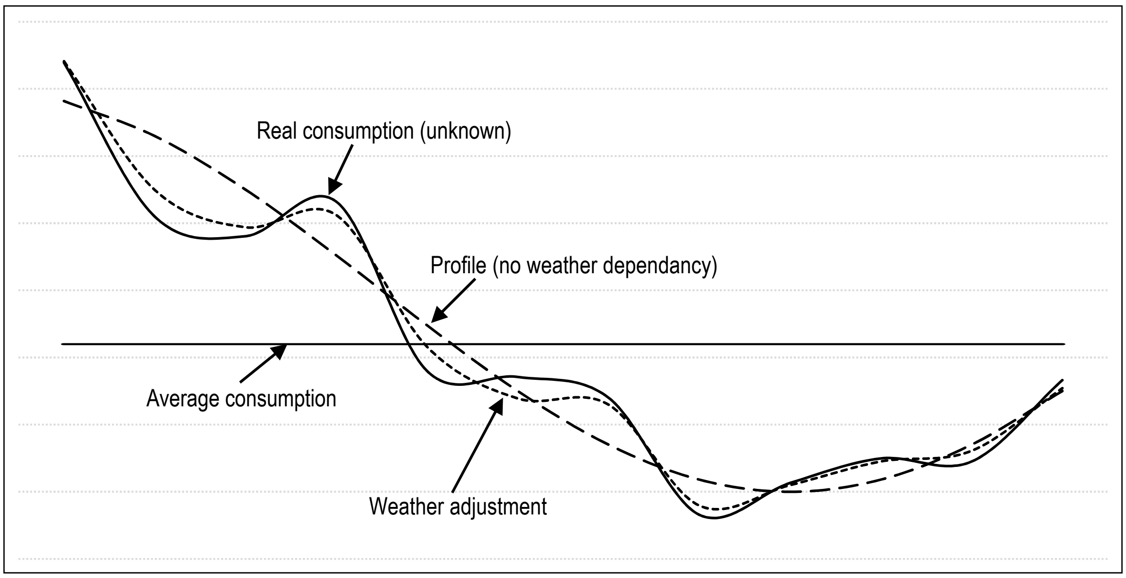
$$Q(j,P) = \frac{1}{2}\sum_{i \in P} PM(j,i) = PM_Y(j) \cdot C(j,i)$$

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 I illustrates the procedure, displaying the observed average consumption within the observation period, i.e. six months, the actual unknown consumption, the imputed consumption that derives from the application on the coefficients associated to the profile, and the consumption that also takes into account the weather. The latter is assumed to be the best

Figure I – **Illustration of an imputed profile**



Source: Authors illustration, based on "*Annexe F du dispositif de reconstitution des flux*" elaborated by the *Réseau de Transport d'électricité* (RTE, 2015).

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 half an hour for each meter of the dataset and aggregate as needed to obtain daily, weekly, monthly or semi-annual consumption. As a result, we end up with a dataset in which we have recorded the meter identifier; a variable then identifies if consumption occurs during peak/off-peak hours; the calendar month and total consumption during the month. For the period covered, we have about two billions observations.

2.2. Extracting a Sub Sample for the Analysis

Once we have harmonized the observations so that one observation period means the same period for all meters, given the very large number of observations, we extract 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 and indicators of the economic activity in 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 strong endogeneity of 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.

3. 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 AIDS model. In the 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 year and month fixed effects as well as weather and a 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. We add all the variables that help controlling 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 variables such as the average age of the population, the share in the labor force and the share of college educated.

3.1. Price Setting in France

Estimating the demand elasticity of any good or service is a difficult task as price and quantity are generally determined simultaneously at the equilibrium. As such, in a simple regression model such as the one we carry on in this paper, a problem of endogeneity arises that could bias the estimates. That is why other models such as instrumental variable are most often 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 State 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 State to produce and distribute electricity in a regime of quasi-monopoly (ie. 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, now Enedis, was created and kept fully in a State monopoly for the distribution of electricity, while together with EDF, still largely participated and controlled by the State, other companies were allowed to provide electricity 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 State while other companies were allowed to offer different schedules. Those companies though, still face the same prices of EDF at source hence 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 considered as exogenous 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, only a small portion of the French customers had chosen to rely on competition up to 2015. 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]

3.2. One-Price Model

Our preferred specification for the estimation of the price elasticity of demand is a fixed effects regression model in which we control for time variables, i.e. years and months (for seasonality effects as well 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 paid. For customers who pay two prices corresponding to peak and off-peak consumption, the average is calculated by weighting 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

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

All prices are expressed in constant 2005 euros (deflated using the CPI index).

3.3. Two-Price Model

Another set of models estimated, to take into account interesting information on household reaction to the difference in price within different time segments of the day, are the AIDS class of models. We follow Filippini (1995) and replicate his 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 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 expenditure in electricity.

As independent variables, we use the log of the prices of the two time segments and the log of total electricity expenditure in real terms. We repeated the estimation for the whole sample and also distinguishing winter and summer. 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 provides additional information on how customers who face

1. See https://www.cre.fr/Electricite/marche-de-detail-de-l-electricite for a full description.

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.

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 estimated have the following form:

$$w_i = \mu_i + \sum_j \gamma_{ij} \, log\left(P_{ij}\right) + \beta_P \, log\left(\frac{m}{P}\right) + X'\theta$$

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

$$P = \sum_j w_j \, log\left(P_j\right)$$

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:

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

Own price and cross elasticities can be computed as follows:

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

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

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

Finally, the elasticity of substitution is obtained by:

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

4. Results

Table 1 reports the results relative to the one-price model. The price elasticity of the demand of electricity is about -0.8. Our result seems to be in line with estimates obtained in other studies especially for European countries. For example, Krishnamurthy & Kriström (2015) find, using very different data, an elasticity for France of -0.96, quite close to our result. Note 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 those households that need larger power absorption, and therefore, will inevitably consume more, pay more. For this reason, and this effect being impossible to disentangle 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 demand 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 data for winter and summer consumption and look at the elasticity during those two seasons. As we can observe, the price elasticity is higher in winter than in summer. To some extent this may seem counter intuitive as

Table 1 – **Consumption of electricity (One-price model)**

Variable	Coefficient	Standard error
Intercept	0.7769	0.0117
(Natural) Log of average variable price	0.7997	0.0031
(Natural) Log of fix price	1.1044	0.0006
Number of days in which the temperature is below 15 degrees C	0.0002	0.0000
Number of days recorder in the month	-0.0035	0.0001
Time dummies	Yes	
R2	0.2989	

Notes: The dependent variable is the (natural) log of consumption.
Sources: Data from Enedis, authors' calculation.

Table 2 – **Consumption of electricity (One-price seasonal model)**

Variable	Winter		Summer	
	Coefficient	Standard error	Coefficient	Standard error
Intercept	-0.7053	0.0225	0.9075	0.0150
(Natural) Log of average variable price	-1.1611	0.0050	-0.6358	0.0039
(Natural) Log of fix price	1.2279	0.0009	1.0089	0.0007
Number of days in which the temperature is below 15 degree C	0.0002	0.0000	0.0003	0.0000
Time dummies	Yes		Yes	
R2	0.3054		0.2630	

Notes: The dependent variable is the (natural) log of consumption.
Sources: Data from Enedis, authors' calculation.

during winter months customers consume more since they need more electricity for heating. However, heating 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 customers are more sensitive to the price of electricity in the winter. During summer months, the demand of energy is generally lower but often more difficult to be satisfied by alternative sources of energy.

4.1. Almost Ideal 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 (1995) and extend it to a seasonal model as well. The AIDS model provides additional information on how customers shift their consumption from one time-segment to another when the relative price of electricity in those segments changes, and, as such, adds precious information on the behaviour 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. Our estimates are remarkable close to the estimates of Filippini even though our data are for a different country and for a different period (cf. Table 4): especially the price elasticity for peak hours is -1.47 in our study compared to -1.41 in Filippini. Our off-peak elasticity results are instead lower,

Table 3 – **Share of consumption of electricity during peak hours (Two-price AIDS model)**

Variable	Coefficient	Standard error
Intercept	0.1443	0.0009
LogP {peak}	0.3025	0.0002
LogP {off-peak}	0.3025	0.0002
Log(m/P)	0.0087	0.0001
(Natural) log of fix price	0.0328	0.0001
Number of days in which the temperature is below 15 degrees C	0.0001	0.0000
Number of days recorded in the month	0.0031	0.0000
Time dummies	Yes	
R2	0.2974	
Number of observations	16,133,468	

Notes: SYSLIN Procedure Iterative Seemingly Unrelated Regression Estimation.
Sources: Data from Enedis, authors' calculation.

Table 4 – **Price elasticity of electricity demand (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

Sources: Data from Enedis, authors' calculation.

Table 5 – **Price elasticity of electricity demand (Two-price seasonnal 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

Sources: Data from Enedis and Filippini (1995a), authors' calculation.

but still higher than the elasticity for peak hour. This result is quite expected as off-peak corresponds to 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 magnitude of 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 compared 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 consumption during this season is more rigid.

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There is a growing interest in forecasting with more and more precision prices, especially for the consumption of energy and in particular electricity. For the electricity market, the issue is of vital interest because electricity that is produced cannot be stored, hence the importance of avoiding overproduction while guaranteeing a sufficient flow to everyone. The key factor for a good forecast is to understand how consumers react to changes in prices, summarized by the concept of price elasticity of consumption. Within the already large literature on this topic, our main contribution is first to corroborate the results found in the previous literature with a dataset that is massively representative; second, the richness of our data allows for taking into account seasonal differences in the consumption behaviour.

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 a price elasticity of electricity

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 thought to be the least elastic among households.

consumption equal to -0.8, a result remarkably in line with the previous literature. In our second specification we follow Filippini (1995) and estimate an AIDS model, with results that are 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 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 a set of economic variables at the department level.

Our paper also opens some more questions on how to improve further our understanding. The fact that seasonal elasticities are effectively different suggests that there may be considerable differences also across regions of France (south *vs* north, for example). More research on this would probably shed light on a more differentiated model within both time and space, which could help better estimate and forecast the consumption of electricity. □

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APPENDIX

DETAILED RESULTS OF THE REGRESSIONS

Table A-1 – **Full regression for Table 1**

Variable	Coefficient	Standard error
Intercept	0.7681	0.0118
(Natural) Log of average variable price	-0.7992	0.0031
(Natural) Log of fix price	1.1044	0.0006
Number of days in which the temperature is below 15 degrees C	0.0002	0.0001
Number of days recorded in the month	-0.0035	0.0001
Share of people in the labor force	0.4117	0.0066
Average age of population	-0.0083	0.0001
Share of home as main residence	1.2524	0.0033
Share of houses over all dwellings	0.4005	0.0013
Share of college educated	0.0968	0.0032
Share of dwelling built before 1990	-0.5468	0.0106
Oil price	0.0002	0.0000
Time fixed effects	Yes	
Number of observations	19,768,361	
R2	0.2989	

Notes: The dependent variable is the (natural) log of consumption.
Sources: Data from Enedis, authors' calculation.

Table A-2 – **Full regression for Table 2**

Variable	Winter		Summer	
	Coefficient	Standard error	Coefficient	Standard error
Intercept	0.7054	0.0225	0.9075	0.0150
(Natural) Log of average variable price	-1.1611	0.0050	0.6358	0.0040
(Natural) Log of fix price	1.2279	0.0009	1.0089	0.0007
Number of days in which the temperature is below 15 degrees C	0.0003	0.0000	0.0003	0.0000
Number of days recorded in the month	0.0000	0.0005	0.0021	0.0002
Share of people in the labor force	0.7482	0.0105	0.1825	0.0085
Average age of population	0.0086	0.0001	0.0081	0.0001
Share of home as main residence	1.3117	0.0053	1.2192	0.0043
Share of houses over all dwellings	0.4476	0.0021	0.3686	0.0017
Share of college educated	0.0299	0.0051	0.1396	0.0042
Share of dwelling built before 1990	0.6773	0.0168	0.4890	0.0136
Oil price	0.0002	0.0000	0.0002	0.0001
Time fixed effects	Yes		Yes	
Number of observations	8,455,612		11,312,749	
R2	0.3054		0.2630	

Notes: The dependent variable is the (natural) log of consumption.
Sources: Data from Enedis, authors' calculation.