HOUSEHOLD PREFERENCES FOR TIME-OF-USE RATES IN THE PORTUGUESE ELECTRICITY MARKET

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ABSTRACT

This paper contributes to the debate about peak-load pricing by making an analysis of the residential electricity market in Portugal. The results were built on techniques of logit regression complemented by quantile regression. We estimate the probability of choosing the Time-Of-Use electricity rate and the probability of reducing the Monthly Costs of Electricity by switching the rate for different consumer profiles. Factors such as consumer behaviour and knowledge are determinant when it comes to choosing differentiated rates. Our results suggest guidelines for defining policy measures that will promote an effective change in consumption periods and rate choices.

Keywords
Electricity rates, Time-of-use

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1. INTRODUCTION

Electricity generation and supply face the problem of peak-load demand, which consists of different loads of demand throughout the day. To avoid shortage of supply, players need to have enough generation capacity to be able to cope with the high demand periods that occur in the course of the day. This causes very high generation costs during these peaks, which tend to be reflected in consumer costs. A change in the energy paradigm is underway from traditional, polluting energy sources towards clean and renewable ones. However, renewable sources are well known to be characteristically intermittent in generating power, which could worsen generation costs still further. It would therefore seem crucial to analyze the tools that allow generation costs to be controlled, which could be done by acting at the level of demand. The relevance of the study of electricity rates can be seen precisely in this context of the need for demand management.

Two main issues arise concerning the peak-load problem: costs inherent in production and demand management. To ensure a continuous supply of electricity, players incur costs in installing capacity production, which is then idle off-peak (Crew *et al.*, 1995). This is at the basis of the peak-load problem. Indeed, the production costs also incorporate the costs of turning on idle capacity. The policies of peak-load pricing, which predominantly consist of price discrimination based on time, have emerged as a way of mitigating market inefficiency (Viscusi *et al.*, 2005). If the price (rate) is uniform over time, then the quantity demanded rises and falls periodically, as stated by Crew *et al.* (1995). Indeed, the pricing policy may be a relevant tool in electricity demand management by balancing the demand for electricity between peak (highest demand periods) and non-peak (low demand periods) and may consequently have a significant impact on the control of production costs. Electricity pricing policies should provide guidance for individual consumers according to their consumption pattern, when it comes to choosing the best rate (Räsänen *et al.*, 1997). Electricity pricing policies were implemented closely in line with the theory of peak prices (Ortega et al., 2008; and Bartusch et al., 2011). This is considered to be an indication of the regulatory authorities' concern to create mechanisms that will encourage the switch from peak periods to off-peak periods.

Most of the literature deals with electricity pricing problems essentially according to three options: i) Critical Peak Pricing (CPP); ii) Real-Time Pricing (RTP); and iii) Time-of-Use (TOU) rates. CPP rates were studied, for example, by Faruqui and George (2005). CPP rates signal to the consumer the critical times and days (peak periods) for which a higher price is set. These rates can be designed under two formats: Critical Peak Pricing Rates – Fixed (CPP-F); and Critical Peak Pricing Rates – Variable (CPP-V). In CPP-F, critical periods are pre-fixed and disclosed to the consumer. In CPP-V, consumers have the technology that allows them to know when they are in critical periods. RTP rates transmit to the consumer the cost of electricity generation in real time, through the application of technologies in homes (smart grid technology). Electricity prices vary according to instantaneous demand, which allows the consumer to manage consumption. Tanaka (2006) stated that by fixing efficient prices, this pricing option may restrain demand. Authors such as Herter and McAuliffe (2007), Herter (2007), and Faruqui *et al.,* (2009) focused both on CPP and RTP rates. In their turn, TOU rates consist of paying a higher price per kWh consumed during peak periods and a lower price in off-peak periods of consumption. Peak and off-peak periods are fixed in advance. The regulatory authorities incorporate production costs into the rates. This process can take several months or even years (Herter and Wayland, 2010).

The study of the rate structures, and in particular time-of-use rates, has a milestone in the quantitative work of Patrick (1990). Notwithstanding, this continues to be an issue, as the growing literature would indicate, in view of the constraints in energy supply facing modern society (e.g. Newsham and Bowker, 2010; Ericson, 2011; and Vassileva et al. 2012). There is a prevalent view in literature that TOU rates generally reduce peak demand and the need for capacity, even though there is lack of consensus about the magnitude of that effect (e.g. Newsham and Bowker, 2010). In fact, earlier, Patrick (1990) pointed out that the reduction in demand in peak periods changes conversely with the length of the peak period. Under shorter peak periods it is easier either to anticipate or to delay some consumption, which is not true otherwise. In others words, if a consumer wants to satisfy a need and the peak period is too long, then the loss of utility in delaying consumption outweighs the saving of consuming at off-peak times. The author also notes that many of the experiments performed with TOU rates could be questionable given that there is an incentive to participate in the experiment, which varies according to consumption level, and thus introduces bias into the sample. The selection bias could also be a consequence of the fact reported by Train and Mehrez (1994) that the consumption level is deeply affected by the consumer price response of participants in the experiment. Since the participants are aware that they are part of an experiment, this may influence their own consumption, as stated by Herter *et al.* (2007). TOU rates are applied in many countries, such as England, France, Portugal, Spain, and the USA.

The switch to a TOU rate within a context of maintaining the same pattern of demand results in a neutral effect on the production cost, while the possible net payoff for the consumers depends on the structure (namely amplitude of prices) of the TOU rates. The overall effect is dependent on the changes in consumption patterns. Higher flexibility in the consumption of electricity encourages the choice of differentiated rates (Ericson, 2011). Switching from peak periods to other periods depends on the consumer profile (behavior, sensitivity and consumer attitudes), such as noted by Bartusch et al. (2011), and the available structure of TOU rates (Tanaka, 2006). Therefore, understanding the reasons behind the consumers' choice of flat rates or differentiated rates, which vary in line with the periods of consumption, is crucial in designing optimal policies to cope with peak-load problems. This is particularly true in one of the leading countries in renewable energies, which are characterized by intermittent production: Portugal. All these points constitute the main motivation for this study.

Most of the empirical literature is focused on the performance of the TOU rate, using technologies (consumption meters) installed in households. This approach is feasible if, and only if, the incumbent players cooperate, i.e., allow access to that data. Besides the factors traditionally assessed in this literature, such as Train and Mehrez (1994), recent literature (e.g. Ek and Söderholm, 2010; Faruqui and Sergici, 2010 and Vassileva *et al.* 2012) has also been centered on consumer characteristics and their behavior. We follow this recent approach. Ascertaining the features of consumption and of consumers requires collecting primary data. In line with Ek and Söderholm (2010), we proceed by finding out about consumers through the questionnaire technique. As shown by Bartusch et al (2011), for Sweden, the households with TOU rates can make a positive contribution towards decreasing peak period demand.

Our analysis is focused on the residential electricity market in Portugal. Our main objectives are to identify what determines rate choices and the potential savings in the Monthly Cost of Electricity (hereafter MCE) consumption, as well as to identify the factors explaining the electricity costs of residential consumers. To reach these objectives we used econometric techniques of logit and quantile regression.

We contribute to the literature on electricity pricing by collecting primary data based on a very large representative sample. This technique of data collection allowed information to be revealed on a wide range of consumer dimensions. This would provide a deep understanding of the factors and reasons for consumer choice, as far as energy rates are concerned. Controlling for these new drivers, which became available with the questionnaire, allowed us to deepen the study of the complexities of decision-making with regard to the electricity rate. We applied various methodologies that allowed us to test the use of new techniques (quantile regression), as well as assess the consistency of results. In short, we analyze the determinants of the rate choice of Portuguese households, consumer saving behavior and MCE for different levels of consumption. Overall, our results are robust and consistent with the literature, contributing to the academic debate, and useful for policy makers, regulatory authorities, electricity market players and practitioners in the market.

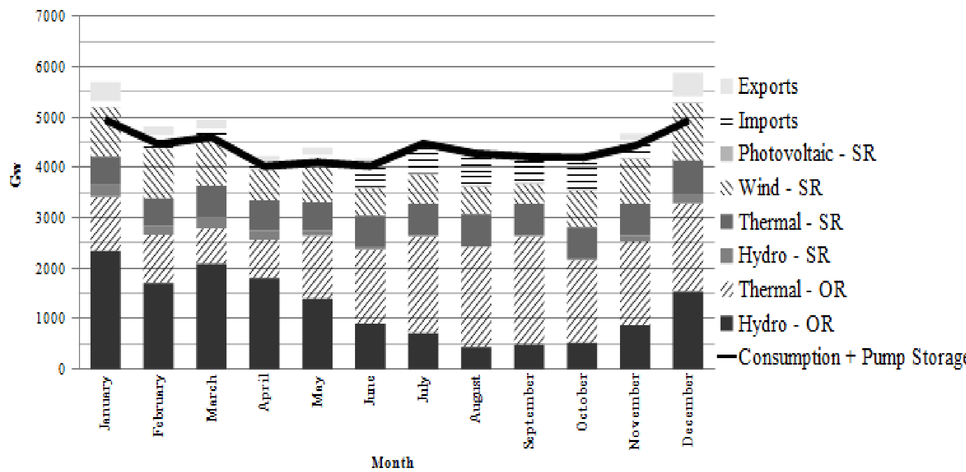
The paper proceeds as follows. In section two we present the Portuguese case. In section three, we present a short discussion of factors. Section four presents and displays the data and methodology. Section five presents a discussion of our results and we finish with our final remarks in section six.

2. THE PORTUGUESE CASE

In Portugal, the main sources of electricity generation are fossil fuels, though the contribution of renewable sources has been growing over the last few years. Figure 1 shows the sources of electricity generation over the year 2010.

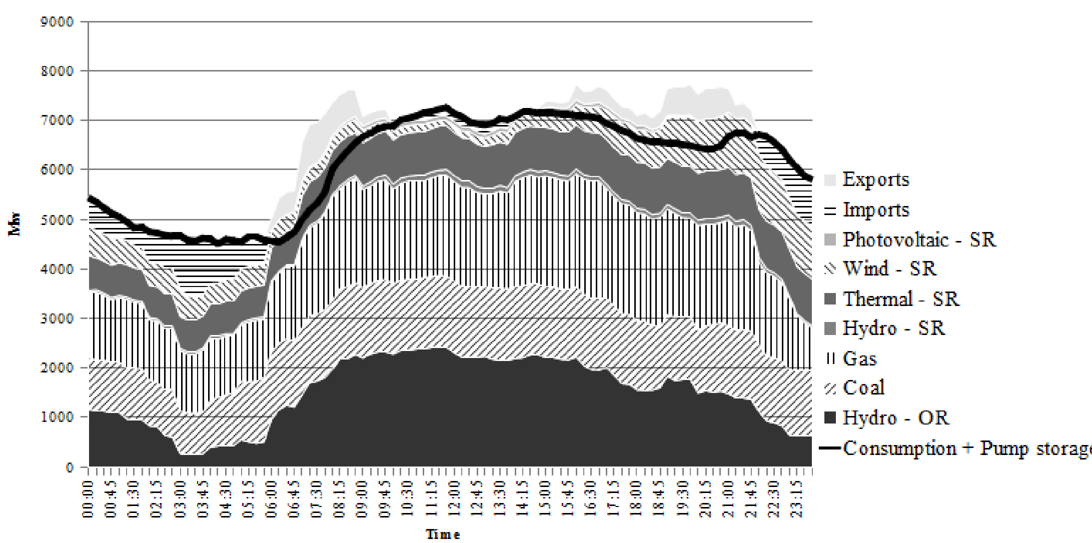
Taking into account a typical day of electricity consumption in Portugal, for example, July 01 2010, Figure 2 shows the electricity generation by source.

On this day, natural gas was the main source of electricity generation, contributing to about 27% of total production, followed by hydro and coal, with 25% and 20%, respectively. As far as renewables are concerned, we can observe that the possibility of water storage was essential in the production of electricity at peak periods.



Notes: Data source: REN – Monthly statistics; SR: special regime generation, which refers to the use of alternative indigenous and renewable sources for electricity generation and for cogeneration; OR: Ordinary regime generation, which refers to the generation of electricity through traditional non-renewable sources and large hydro-electric plants.

Figure 1: Sources of electricity generation over the year 2010



Notes: Data source: REN. We select randomly a typical day of electricity consumption (01/06/2010). SR: special regime generation, which refers to the use of alternative indigenous and renewable sources for electricity generation and for cogeneration; OR: Ordinary regime generation, which refers to the generation of electricity through traditional non-renewable sources and large hydro-electric plants.

Figure 2: Electricity generation by source, in Portugal.

Excluding hydro, with about 22%, the renewable sources contribute to electricity generation as follows: thermal - 13%; wind - 8%; and solar 1%. It is worth noting that their contributions are unstable throughout the day. At certain periods of the year, the intermittency of electricity generation from renewable sources is more pronounced, which requires better management of demand and of the electricity generation sources. From Figure 1, we observe that decreasing water levels between May and October coincide with a drop in the production of wind energy. This increases the need to use non-renewable energy sources, such as thermal energy fuels (gas and coal). The electricity retail market is segmented into: i) liberalized market; and ii) regulated market. In the liberalized market, efforts have been made to extend the operation of the Iberian Electricity Market (MIBEL). It has existed in Portugal since July 1 2007 and in March 2010 accounts for 297,615 customers. The major players operating within this market are EDP, Endesa, Iberdrola and Union Fenosa, providing just flat rates.

In the regulated market, the *Entidade Reguladora dos Serviços Energéticos* (ERSE) is the regulatory authority. Three rates of low voltage are available to consumers. These are the flat rate, with the same price throughout the day, and two optional types of rates according to the Time of Use (TOU rates): i) one that splits the day into two periods of time (peak and off-peak periods) - bi-hourly rate; and ii) another that splits the day into three time periods (high-peak, peak and off-peak) - tri-hourly rate. The flat rate is the same as the standard rate that existed prior to the existence of the TOU rate, with the prices defined by the regulatory authority, in accordance with the marginal costs. In Table 1 we present the peak periods. Portugal has two choices when it comes to TOU rates. In fact, consumers can choose from a daily cycle or weekly cycle. In the daily cycle, peak period remains constant throughout every day of the week; in the weekly cycle there are some variations depending on the day of the week. The option for flat or TOU rates is voluntary.

Table 1. The length of peak, in Portugal (adapted: rates 2010 - EDP).

	Winter	**Summer**
	Weekly cycle	
	Monday - Friday	
Length of peak	07.00. – 24.00	07.00 – 24.00
Length of high peak	09:30. – 12.00 18:30. – 22.00	09:15 – 12:15
	Saturday	
Length of peak	09:30. – 13.00 18:30 – 22.00	09:30 – 13.00 20.00 – 22.00
	Sunday	
Length of peak	-	-
	Daily cycle	
	Monday - Sunday	
Length of peak	08.00 – 22.00	08.00 – 22.00
Length of high peak	09.00 – 10:30 18.00 – 20.30	10:30 – 13.00 19.30. – 21.00

The flat rate is the choice of most consumers, followed by the bi-hourly rate. The three-time option (tri-hourly rate) is very recent (available to consumers since January 1, 2009) and is therefore, still the option of only a very small group of consumers. Table 2 summarizes the rate prices.

Table 2. Rates of the regulated Portuguese electricity market, EUR/kWh) (adapted: rates 2010 - EDP).

Rates	High Peak	Peak	Off-peak
Flat rate	0.1285	0.1285	0.1285
TOU (bi-hourly rate)	0.1382	0.1382	0.0742
TOU (tri-hourly rate)	0.1520	0.1332	0.0742

We can see the attractiveness of the TOU rate compared to the flat rate. Consumers pay 0.0097 EUR\kWh more at peak times, but can save 0.0543 EUR\kWh in off peak periods. However, the tri-hourly rate loses attractiveness to the bi-hourly rate. They have the same off-peak rate, and the period length is equal. The only differences are out of the off-peak. While the price at peak time is 0.005 EUR\kWh lower in the tri-hourly rate, the high peak price is greater by 0.0138 EUR\kWh. In this paper, we only consider the regulated market and the two-time option of the TOU rates.

3. DETERMINANTS OF CONSUMER PREFERENCES

Traditionally, the literature focused on analyzing the TOU rate was based on consumer meters, typically positioned in the place of consumption (e.g. Aigner and Ghali, 1989). However, recent studies (e.g. Ek and Söderholm, 2010) shed light on new consumer dimensions, such as their lifestyle, in order to understand new drivers which are not captured by consumption meters. Indeed, nowadays, consumer decisions are central in the whole electricity market and, consequently, it is essential to have a full understanding of their decisions, not only for optimal electricity demand management but also for optimal production management. This has motivated the gathering of primary data, i.e., the use of individual questionnaires allows an understanding of the several factors influencing consumer decisions. Other field methods, such as interviews or focus groups, prove not to be feasible in collecting a large database. Accordingly, we follow the literature (e.g. Matsukawa, 2001; McDonough and Kraus, 2007; and Gamble *et al.*, 2009; Ek and Söderholm, 2010) to define the explanatory variables, which are grouped into four factors: 1) socioeconomic; 2) house characteristics; 3) behavioral; and 4) knowledge and environment. The variables and their definitions are presented in section 4, below.

3.1 Socioeconomic Factor

When it comes to assessing consumption decisions, it is expected that socioeconomic variables are effective. This is equally true for electricity consumption, as shown, for example, by Train and Mehrez (1994), Matsukawa

(2001), Ek and Söderholm (2008) and Abrahamse and Steg (2009). Following the literature, the socioeconomic factor groups the variables income, monthly household cost of electricity, consumer age, the number of household members and the level of education. It is expected that this factor will provide a better understanding of the choice of rate and of the savings that consumers can achieve with a change in rate. This could also be crucial in explaining the monthly cost of electricity.

Income can lead to two distinct effects. On the one hand, a higher income allows greater consumption and consequently higher electricity bills. On the other hand, higher income can also allow ways of saving to be found, such as the acquisition of more efficient technologies. For households with higher monthly electricity costs, it is expected that they will be more prone to switching periods of consumption, in order to get absolute savings from the change to TOU rates, which rewards off-peak consumption. Actually, lower electricity bills may dissuade consumers from trying to find ways to reduce monthly electricity costs. In absolute terms, larger numbers of people in the household lead to higher electricity consumption. However, even if each member could shift consumption to off-peak periods only by a small percentage, the aggregate shift of consumption of the household would be relevant, in absolute terms. The level of education can also be relevant to the option for TOU rates, because consumers have more knowledge as well as more awareness of the benefits of access to information.

3.2 House Characteristics Factor

Electricity consumption is linked to the physical characteristics of consumers' houses, i.e., to the idiosyncratic characteristics of the place of consumption. Accordingly, in this factor, we control for the variables that specify the number and type of appliances, the use of air conditioning, the water heating system, and the size and type of housing.

Large numbers of electrical appliances could increase the monthly electricity cost, and reveal consumer preference for the use of electricity in detriment to other energy sources, such as gas. In this way, it is expected that greater sensitivity to the cost of consumption in different periods increases the propensity to subscribe to TOU rates. On the other hand, if the appliances are efficient in consumption, then the monthly electricity cost may not be high enough to awaken the need to switch consumption to off-peak. The use of air conditioning tends to increase the electricity bill substantially, as shown by Faruqui and George (2005). This equipment incorporates timer programming technology which allows flexible control of time consumption. In other words, this equipment matches reasonably well with the structure of TOU rates. A similar phenomenon is expected for electrical water heating equipment. With regard to the type of house, e.g. apartment or detached house, distinct effects could be expected. Indeed, different houses (e.g. size and type) might require different levels of consumption, which could influence the choice of rate. In fact, living in a house can mean higher electricity costs, e.g. outdoor lighting, which can increase the probability of opting for a TOU rate.

3.3 Behavioural Factor

The switching of consumption to off-peak periods will depend on consumer behavior as well as on how rates are designed, as pointed out by Tanaka (2006), and this is a crucial point in dealing with the peak demand problem. In fact, as shown by Train and Mehrez (1995), consumers who opt for TOU rates, but retain the same kind of demand, are not contributing to solving the problem, because production costs remain the same. Accordingly, we are seeking to understand the actual conduct of the consumers and how they make their consumption decisions.

Consumers are asked which time periods (e.g. morning or afternoon) they consider to be more intensive in electricity consumption. We then assess whether there are changes in consumption habits (for example if consumers leave electronic devices on standby), once a change from a flat to a TOU rate has been made. A full understanding of this behavioral factor will be important for the design of pricing policies to encourage a switch in consumption.

A change in consumer habits (and comfort) could be dependent on the compensation available, that is, it could be dependent on the price difference between peak and off-peak (Gallant and Koenker, 1984). However, as noted by Räsänen *et al.*, (1997) if this difference is small, then the incentive to make the switch in consumption, from peak to off-peak, may not be good enough. In the same way, as stated before, the length of peak time is conversely related to the reduction in consumption during that period (Patrick, 1990).

It is expected that consumers with low peak demand are more likely to choose a TOU rate, unlike consumers with high demand during this period, as stated by Train and Mehrez (1995). Consumers with high off-peak demand are more likely to choose a TOU rate, in contrast to consumers with lower demand during this period. Consumers with more ability to switch periods of consumption are also more likely to choose a TOU rate.

3.4 Knowledge and Environment Factor

The variables in the knowledge and environment factor aim to evaluate the effects of full consumer understanding of the electricity market on their own decisions. Moreover, this factor attempts to assess to what extent consumers subscribe to renewable energy production systems. Consumers reveal not only environmental concerns but also deep knowledge of the financial objectives of benefitting from the public incentives for renewables. Under this factor we control for variables such as the self-perception of efficiency, familiarity with electricity production costs, the use of efficient light bulbs or the status of renewable energy producers.

This leads to the question: *Is the level of knowledge revealed by consumers about the electricity market favoring the option for TOU rates*? It is to be expected that information and social responsibility would contribute positively to the option for TOU rates. Moreover, as Matsukawa (2004) showed, when consumers are informed about their electricity consumption, they are more likely to reduce consumption. It is also expected that consumers who simultaneously produce electricity through micro-electricity generation from renewable sources are most likely to choose the TOU rates.

4. DATA AND METHODS

This paper collected data using the questionnaire technique. A similar technique was also used by Ek and Söderholm, 2010 and Abrahamse and Steg, 2009. The questionnaires were applied to the households with an electricity purchasing contract (low voltage contracts from 2.3 kVA to 20.7 kVA) in order to get a representative random sample. To do so, the sample covers mainland Portugal, namely the regions: North, Centre, Lisbon, Alentejo and Algarve. This universe consists of about three and a half million households (*Instituto Nacional de Estatística* (INE), November 2009). The pretest was conducted in December 2009, which enabled us to define the time response of the questionnaire, the respondent's attitude towards the questions, the full understanding of the questions, filters in order to appraise the consistency and coherence of the responses (Hill and Hill, 2005).

The data was gathered online, by phone and face-to-face. The questionnaire published online was conducted by using the building surveys tool and on-line availability of Google (spreadsheets), from December 2009 to March 2010, and obtained responses representing about 80% of the sample. The phone contributed with 15% of the responses. The questionnaire conducted face-to-face represented 5%. We validated 2,569 (77.5%) questionnaires of the 3,314 collected. With this universe and with a sample of 2,569 surveys, the margin of error was 1.93%, for a confidence level of 95%.

Regarding the design of the questionnaire, the proper fit between the objectives of the study and the questionnaire was found, and so were the questions that correspond to each of the factors: housing characteristics, behavioral, and knowledge and environment. The collected sample and the expected sample are described in Table 3.

Table 3. Sample provided and collected through questionnaire.

Regions INE	Households	Sample			
		Collected		Expected	
North	1211550	692	27%	691	35%
Centro	848286	765	30%	483	24%
Lisbon	1006810	721	28%	574	29%
Alentejo	292898	188	7%	167	8%
Algarve	149369	203	8%	85	4%
Total	3508913	2569	100%	2000	100%

Table 4 defines the variables and their measurements, and summarizes their descriptive statistics. In the questionnaire, the respondent marks whether his choice of rate is TOU or Flat. The RATE variable is equal to 1 if it is a TOU rate and 0 if not.

Table 4. Data: definition and summary statistics.

Variable	*Definition*	*Obs.*	*Mean*	*SD*	*Min*	*Max*
RATE	Equal to 1 if TOU rates and 0 if not	2569	0.42	0.49	0	1
Socioeconomic factor						
INCOME	Monthly income of household by level;	2495	3.66	1.57	1	6
COST	Monthly household electricity cost, in EUR;	2557	53.98	31.35	10	200
AGE	Age of respondent;	2488	37.05	11.04	18	81
PERSONSBELOW18	Percentage of people aged under 18 in household;	2569	0.18	0.22	0	0.8
NPERSONS	Number of household members;	2569	2.97	1.17	1	10
SECSCHOOL	Equal to 1 if respondent has only secondary education;	2569	0.15	0.36	0	1
UNIVERSITY	Equal to 1 if respondent has university level.	2569	0.61	0.49	0	1
House characteristics factor						
APPLIANCES	Number of housing appliances;	2569	13.21	2.94	2	26
AC	Equal to 1 if there is air conditioning;	2569	0.20	0.40	0	1
WASHMACHINE	Temperature using the washing machine;	2513	1.92	0.71	0	4
WATERHEATER	Equal to 1 if there is electric water heating;	2569	0.11	0.31	0	1
APARTMENT	Equal to 1 if apartment is the type of housing;	2481	0.60	0.49	0	1
DETACHEDHOUSE	Equal to 1 if detached house is the type of housing;	2481	0.32	0.47	0	1
HOUSESIZE	House size by level;	2397	7.43	2.24	1	12
GARDEN	Equal to 1 if there is a garden;	2569	0.36	0.48	0	1
ELECTRICOVEN	Equal to 1 if there is an electric oven;	2569	0.75	0.43	0	1
ELECTRICOOKER	Equal to 1 if there is a cooker or hot plate;	2569	0.61	0.49	0	1
EFFICAPPLIANCES	Equal to 1 if using efficient appliances.	2569	0.92	0.28	0	1
Behavioural factor						
WEEKENDPEAK	Equal to 1 if – energy consumption in peak hours – weekend;	2569	0.77	0.42	0	1
MORNING	Equal to 1 if – energy consumption in the morning (8am-1pm) – Week;	2569	0.15	0.36	0	1
AFTERNOON	Equal to 1 if – energy consumption in the afternoon (1pm-6pm) – Week;	2569	0.06	0.24	0	1
DINNER	Equal to 1 if – energy consumption at dinner time (6pm-10pm) – Week;	2569	0.85	0.36	0	1
OFF-PEAK	Equal to 1 if – energy consumption in off-peak periods (10pm-8am) – Week;	2569	0.34	0.47	0	1
STANDBY	Equal to 1 if electronic devices are left on standby;	2569	0.51	0.50	0	1
SAVING	Equal to 1 if respondent saved by switching rate;	950	0.69	0.46	0	1
CONSROUTINES	Equal to 1 if consumer has changed consumption routines.	1210	0.74	0.44	0	1
Knowledge and environment factor						
EFFICCONSUMER	Equal to 1 if consumer is considered energy efficient;	2569	0.59	0.49	0	1
COSTPROD	Equal to 1 if respondents know that the cost of electricity production varies throughout the day;	2569	0.81	0.39	0	1
EFFICBULB	Equal to 1 if respondents know the reason for encouraging the use of efficient light bulbs;	2569	0.73	0.44	0	1
STOPPROD	Equal to 1 if respondents know that production varies throughout the day;	2569	0.32	0.47	0	1
INFOSUM	Level of information by level;	2569	1.87	0.90	0	3
RENEWSYSTEMS	Equal to 1 if using renewable energy systems.	2569	0.11	0.31	0	1

Table 4 Notes: Variables Level, **INCOME:** 1: 0EUR -500EUR; 2: 501EUR - 1000EUR; 3: 1001EUR - 1500EUR; 4: 1501EUR - 2000EUR; 5: 2001EUR - 2500EUR; 6: more than 2500EUR. **HOUSESIZE** in m^2: 1: 0 – 15; 2: 15-30; 3: 30-45; 4: 45-50; 5: 50-65; 6: 65-80; 7: 80-100; 8: 100-150; 9: 150-200; 10: 200-300; 11: 300-500; 12: more than 500. **INFOSUM:** 0 – Not informed; 1 – Little informed; 2 – Informed; 3 – Well informed. **WASHMACHINE:** 1- Below 30º; 2 - Between 30 and 40; 3 - Between 40 and 60; 4 - Greater than 60.

From a first inspection of the collected data, we observe that the flat rates and TOU rates represent 58% and 42%, respectively, of residential consumers of electricity. On average, consumers are 37 years old and households are composed of three members. The average monthly income is in the range from EUR 1500 to EUR 2000, which is in accordance with the results given to the media by the INE (2008) on March 31, in which the average monthly income of Portuguese households was EUR 1845.

Both the subscription to TOU rates and electricity consumption increase as income rises. At the same time, we observe that the monthly cost of electricity and the choice of TOU rates vary in the same direction. With respect to consumption habits, the data coincides with that shown by the ERSE and *Rede Eléctrica Nacional* (REN) and INE. The period with the highest electricity consumption is between 07.30 and 22.00. The consumption of electricity reveals a more homogeneous distribution throughout the weekend than on working days, except for the period from 19.30 to 22.00.

The data and methodology allow us to: i) analyze the determinants of electricity rate choice for private households; ii) identify the factors leading to electricity saving, after confirming the rate switch; and iii) assess the determinants of the cost of electricity consumption for different levels of spending.

In order to deal with these goals, two techniques are applied: binary outcome models and quantile regression approach. Firstly, by using a logit model, we study the choice between the flat rate and the rate evolving in accordance with the time of consumption (TOU rates). Secondly, given a change in the choice of rate, we estimate the factors allowing for electricity cost saving. We finish by looking at the MCE determinants using quantile regression. The econometric package Stata 11.1 was used.

The logit model is an econometric methodology of qualitative choice. We define y_i^* as the latent variable, non-observable and continuous, such that, $y_i^* = X_i\beta + \mu_i$ with $\mu_i \sim N(0, \sigma^2)$, the random error term for observation *i*. The X_i is the matrix of the variables of socioeconomic factor, house characteristics factor, behavioral factor, knowledge and environmental factor. The problem of binary choice is represented by a binary observed variable y_i, which is defined as $y_i = 1$ if $y_i^* > 0$ and $y_i = 0$ if $y_i^* \leq 0$.

We also estimate a family of conditional quantile functions, which gives us a complete picture of covariate effects (Koenker and Hallock, 2001). In fact, the results of quantiles regression are robust to outliers and heavy-tailed distributions. The Ordinary Least Squares (OLS) estimation focuses on the average monthly consumption of electricity, while the quantile regression allows us to understand the whole conditional distribution of MCE in the household market. This technique enables us to see which factors influence the expense for each level of electricity bill, while it is particularly relevant in understanding whether these determinants are maintained for any level of consumption, as well as recognizing the factors that influence very low and very high costs.

The quantile regression model, particularly the τ^{th} regression quantile, $0 < \tau < 1$ solves the problem:

$$\min_{\omega_\tau}\left\{\sum_{i:y_i \geq x_i^{'}\omega}^{N} \tau\left|y_i - x_i^{'}\omega\right| + \sum_{i:y_i < x_i^{'}\omega}^{N} (1-\tau)\left|y_i - x_i^{'}\omega\right|\right\}.$$

The quantile regression estimates the marginal impact of vector X_i denoting the independent variables on the MCE at the conditional quantiles cost distribution. To obtain heteroscedasticity-robust estimates, we report robust standard errors for OLS estimates.

When working with a lot of variables good econometric practices strongly recommend a careful assessment of both endogeneity and collinearity phenomena. Diagnosis of the possible presence of "endogenous variables" (*ivprobit* - command) strongly suggests that there are "no endogenous variables". Regarding collinearity, its assessment is relevant in order to assure the consistency of the parameters' estimates. Correlation matrixes are shown in the Appendix, in accordance with the three models presented in the next subsections 4.1, 4.2, and 4.3. These matrixes suggest that, overall, the problem of collinearity is absent for all variables[1]. Furthermore, given the large number of variables, it makes sense to provide a global test of collinearity. The whole VIF tests suggest that collinearity is no concern whatsoever. The mean VIF is always far from 5, indicating that collinearity is far from a concern in our models.

4.1. Consumer Choice of Electricity Rate

By applying the model of logit regression - in models *I, II* and *III* - we analyze the determinants of a household's choice of electricity rates[2]. The dependent variable is the type of contracted rate (RATE). It is a binary variable that takes the value of one (1) when the contracted rate is the TOU rates and 0 otherwise. In model *I* we start by introducing variables extensively tested by the literature (Ek and Söderholm, 2010; Herter, 2007; and Faruqui *et al.*, 2009). Model *II* shows two specific types of housing in Portugal and consumer behavioral factor. In model *III* variables of the knowledge and environmental factor were tested. Table 5 illustrates the results, the changes in probabilities for choice of rates (Min→Max), the marginal effects and the expected sign of each explanatory variable.

The validity of the estimations is stressed by applying a set of tests. The Hosmer-Lemeshow Goodness-of-Fit test was performed. Setting the number of groups at four, we do not reject the hypothesis of good specification. We repeat the test for three and six groups. Nevertheless, the test suggests good specification of model *III*, allowing us to conclude that the model is appropriate. We also assess the fit of model *III*, by using the Bayesian Information Criterion (BIC). Comparing models *II* and *III*, we see that the absolute difference is 14.27. There is very strong support for using model *III*.

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[1] There are a few exceptions, such as UNIVERSITY and SECSCHOOL (subsection 4.1). In those cases, we re-estimate the models with and without those variables. There is no change in the signals of the effects, which is an additional signal of the robustness of our results.

[2] We also studied probit and cloglog models. Their estimated coefficients allow similar conclusions regarding the impact of the regressors in the Pr (RATE = 1).

Table 5. The choice of electricity rates, changes in probabilities for consumer choice of rates, marginal effects and expected sign.

Dependent variable – *RATE*

Independent variables	*Model I*	*Model II*	*Model III*	*Min→Max*	*Marginal effects*	*Expected Sign*
Socioeconomic Factor						
INCOME	0.12*** (0.03)	0.12*** (0.03)	0.12*** (0.03)	0.14	0.03*** (0.01)	+
COST	0.004*** (0.002)	0.005*** (0.002)	0.006*** (0.002)	0.29	0.002*** (0.0005)	+
PERSONSBELOW18	0.93*** (0.20)	1.18*** (0.22)	1.16*** (0.22)	0.23	0.28*** (0.054)	+
SECSCHOOL	-0.52*** (0.15)	-0.48*** (0.16)	-0.43*** (0.16)	-0.10	-0.10*** (0.04)	-
UNIVERSITY	*n.s.*	*n.s.*	*n.s.*	*n.s.*	*n.s.*	+
House Characteristics						
APPLIANCES	0.12*** (0.02)	0.11*** (0.02)	0.10*** (0.02)	0.02	0.02*** (0.01)	+
AC	0.35*** (0.11)	0.34*** (0.11)	0.36*** (0.12)	0.09	0.09*** (0.03)	+
APARTMENT		*n.s.*	*n.s.*	*n.s.*	*n.s.*	+\-
DETACHEDHOUSE		*n.s.*	*n.s.*	*n.s.*	*n.s.*	+\-
ELECTRICOVEN			*n.s.*	*n.s.*	*n.s.*	+
ELECTRICOOKER			*n.s.*	*n.s.*	*n.s.*	-
EFFICAPPLIANCES			0.40** (0.1874)	0.09	0.09** (0.04)	+
Behavioral Factor						
WEEKENDPEAK		-0.24** (0.12)	-0.25** (0.12)	-0.06	-0.06** (0.03)	-
MORNING		-0.31** (0.14)	-0.34** (0.14)	-0.08	-0.08*** (0.03)	-
AFTERNOON		-0.46** (0.23)	-0.44** (0.23)	-0.10	-0.10** (0.05)	-
DINNER		-0.63*** (0.16)	-0.60*** (0.16)	-0.15	-0.15*** (0.04)	-
OFFPEAK		1.25*** (0.11)	1.27*** (0.11)	0.31	0.31*** (0.02)	+
STANDBY			*n.s.*	*n.s.*	*n.s.*	-
Knowledge and Environment Factor						
EFFICCONSUMER			0.37*** (0.10)	0.09	0.09*** (0.02)	+
COSTPROD			0.58*** (0.13)	0.14	0.14*** (0.03)	+
EFFICBULB			*n.s.*	*n.s.*	*n.s.*	+
STOPPROD			-0.22** (0.11)	-0.05	-0.05** (0.03)	+
CONS	-2.66*** (0.24)	-2.13*** (0.35)	-3.07*** (0.41)			
N	2412	2331	2331			
McFadden's R^2	0.071	0.156	0.171			
W-Chi^2	198.13 (0.000)	378.29 (0.000)	386.54 (0.000)			
LR *test*			47.77 (0.000)			
Joint significance test		245.10 (0.000)	44.39 (0.000)			
H-L gof test (4)			2.23 (0.3276)			
Count R^2	0.65	0.70	0.71			
BIC			14.27			

Table 5 Notes: The Wald test has $\chi 2$ distribution and tests the null hypothesis of non-significance of all coefficients of explanatory variables; The Likelihood Ratio test has $\chi 2$ distribution and tests the null hypothesis that the restricted model (*II*) is the best model; The joint significance test is a test *Wald* (χ^2), under the null hypothesis of $H_O : \beta_i = 0$, with $i = i...k$ for the *k* variables. Min→Max means change in predicted probability as the variable changes from its minimum to its maximum; The marginal effects presented are calculated for the average of the variables $X = \bar{X}$; BIC: Bayesian Information Criterion; ***, **, denote significance at 1, and 5 significance levels, respectively; robust standard deviations are reported in brackets. "n.s".: denote not significant.

This deeply suggests the appropriateness of adding the explanatory variables *ELECTRICOVEN, ELECTRICOOKER*, *EFFICAPPLIANCES*, *STANDBY* and knowledge and environmental into the model. The count R^2 indicates that the consumer rate choice is correctly classified in 71.2% of cases. The sensitivity, i.e., the fraction of consumers with TOU rates identified correctly, is 0.58. The specificity, i.e., the proportion of flat rate identified correctly by the logistic regression model, is 0.82.

Analyzing the McFadden R2, model *III* predicts the consumer's choice for the electricity rate in a better way. From the Likelihood Ratio (LR) test we reject the null hypothesis, that is, the test suggests that there is no evidence that the restricted model (model *II*) is the best model, compared to the unrestricted (model *III*). In this way we conclude that model *II* does not retain enough relevant information to dispense with the unrestricted model. Therefore, it is highly advisable to focus on model *III*. We also provide a joint significance test, both for model *II* and model *III*. In both cases, the tests reinforce that the specification of model *III* is adequate. In other words, the proposed model (*III*) proves to be the appropriate model to explain the choice of electricity rate. The results suggest that the effect of variables, such as income, MCE, the percentage of people aged below 18 years in the household, number of appliances and air-conditioning are consistently positive and statistically significant in the three models. A consumer with the maximum number of appliances, when compared to others with the minimum number of appliances, has a 0.53 higher probability of choosing TOU rates. The sign of the monthly cost effect on the choice of TOU rates is what is expected, but, surprisingly, its marginal effect is weak.

The impact of the behavioral factor on the option for TOU rate is jointly effective. Consuming in off-peak periods increases the possibilities of subscribing to TOU rates, as expected. Consumption in peak periods decreases the likelihood of signing up for TOU rates.

By testing the variables of the knowledge and environmental factor, the consistency of models remains unchanged. The use of efficient equipment is correlated with TOU rates. On the other hand, the use of *ELECTRICOVEN* and *ELECTRICOOKER* is not statistically significant, like the variable *STANDBY*. This result suggests consumer indifference regarding the period of consumption, particularly when it comes to leaving the equipment connected to the electric supply. The notion of efficient consumption and the perception of different costs of electricity production throughout the day are positive and statistically significant at 1%.

4.2 Savings From Rate Switching

Once the rate change has been confirmed, factors leading to electricity saving are identified. The concept of electricity saving used here is that of perceptions self-reported by consumers in the questionnaires. The variable *SAVING* is binary, assuming the value of one (1) when consumers reduced their electricity bill after changing their rate (from flat rate to TOU rate). Two models of saving were estimated - Model *IV* and *V*. In model *V* we tested variables of the behavioral, knowledge and environmental factor.

Table 6. Saving from rate switching, changes in probabilities for consumer savings, marginal effects and expected sign.

Dependent Variable – *SAVING*

	MODEL IV	*MODEL V*	*Min→Max*	*Marginal effects*	*Expected Sign*
RATE	2.73***	2.68***	0.58	0.58***	+
	(0.25)	(0.24)		(0.05)	
Socioeconomic Factor					
INCOME	0.13**	0.12**	0.12	0.02**	+
	(0.06)	(0.06)		(0.01)	
NPERSONS	*n.s.*	*n.s.*	*n.s.*	*n.s.*	+
House Characteristics					
WASHMACHINE	*n.s.*	*n.s.*	*n.s.*	*n.s.*	+
AC	*n.s.*	*n.s.*	*n.s.*	*n.s.*	+
APARTMENT	*n.s.*	0.72**	0.14	0.14**	+\-
		(0.37)		(0.07)	
DETACHEDHOUSE	*n.s.*	*n.s.*	*n.s.*	*n.s.*	+\-
ELECTRICOVEN	*n.s.*	*n.s.*	*n.s.*	*n.s.*	+
ELECTRICOOKER	*n.s.*	*n.s.*	*n.s.*	*n.s.*	-
WATERHEATER	*n.s.*	*n.s.*	*n.s.*	*n.s.*	-
GARDEN	0.80***	0.93***	0.16	0.16***	+
	(0.30)	(0.31)		(0.05)	
Behavioral Factor					
OFFPEAK		*n.s.*	*n.s.*	*n.s.*	+
CONSROUTINES	1.62***	1.52***	0.33	0.33***	+
	(0.22)	(0.22)		(0.05)	
Knowledge and Environment Factor					
EFFICCONSUMER		*n.s.*	*n.s.*	*n.s.*	+
RENEWSYSTEMS		*n.s.*	*n.s.*	*n.s.*	+
INFOSUM		*n.s.*	*n.s.*	*n.s.*	+
CONS	-4.53***	-5.26***			
	(0.66)	(0.72)			
N	855	855			
McFadden's R^2	0.288	0.299			
W-Chi²	297.78	309.21			
	(0.000)	(0.000)			
LR *test*		11.43			
		(0.0221)			
Joint significance test		11.24			
		(0.000)			
Pearson gof test (4)		849.79			
		(0.1800)			
Count R^2	0.82	0.83			

Table 6 Notes: The Wald test has $\chi 2$ distribution and tests the null hypothesis of non-significance of all coefficients of explanatory variables; The Likelihood Ratio test has $\chi 2$ distribution and tests the null hypothesis that the restricted model (*II*) is the best model; The joint significance test is a test *Wald* (χ^2), under the null hypothesis of $H_0 : \beta_i = 0$, with $i = i...k$ for the *k* variables. Min→Max means change in predicted probability as the variable changes from its minimum to its maximum; The marginal effects presented are calculated for the average of the variables $X = \overline{X}$; ***, **, denote significance at 1, and 5 significance levels, respectively; robust standard deviations are reported in brackets. "n.s".: denote not significant.

Table 6 reveals the results, the changes in probabilities of consumers saving on monthly electricity bills (Min→Max), the marginal effects as well as the expected sign of each explanatory variable.

Looking at the McFadden R^2, model *V* better predicts the consumer savings according to the choice of rate than model *IV*. This evidence is also supported by the LR test, i.e., there is no evidence that the restricted model *IV* is the best model, when compared to the unrestricted model *V* and therefore this model *V* is the appropriate model to explain the savings from changes in the rate option. The joint significance test suggests that, together, the explanatory variables added to model *V* are statistically highly significant.

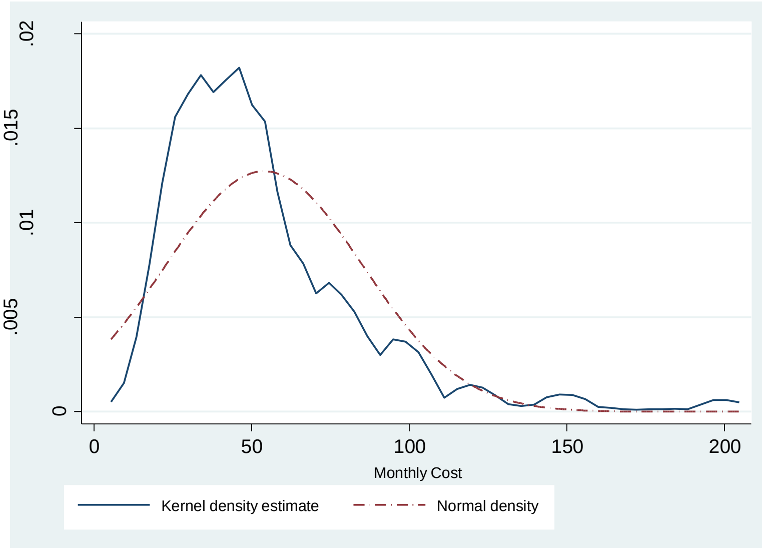
The results show that the type of rate, the income, living in an apartment, having a garden and changing consumer routines are statistically significant variables, contributing to making savings. The probability of savings increases by 0.58 and 0.33 with the change to TOU rates, and with the change of consumption routines, respectively.

Variables such as the *ELECTRICOVEN*, *OFFPEAK* as the period of high consumption and *EFFICCONSUMER* are positive and statistically significant only at 10% in model *V*. For example, for a household with three members that has the TOU rates, the probability of savings increases by 0.58 against a household with the same number of members not having the TOU rates. In general, the marginal effects take the expected values. Variables such as *RATE* and *CONSROUTINES* reveal the effects with greatest magnitude.

4.3 Monthly costs of electricity consumption

We now intend to understand the factors that influence the MCE. We analyze the electricity consumption, not just for the average consumer, but also for consumers who are located at the tails of the distribution. We focus on consumers with a very low monthly expense, and on those for whom the cost of electricity is very high.

Figure 3 shows the Kernel density estimate for MCE, suggesting that the conditional distribution does not follow a Gaussian distribution. The assumption of normality is rejected both by the Shapiro-Wilk test and by the Skewness-Kurtosis test, for a significance level of 1%. The OLS procedure is therefore not appropriate. In contrast, quantile regression, first introduced by Koenker and Basset (1978), is suitable due to its asset of robustness in the absence of normality, as is the case. This allows us to estimate the effects of various factors at different points of the conditional distribution of the MCE.



Notes: Epanechnikov kernel density estimated is presented. The kernel density bandwidth is set to 4.5835.

Figure 3: Estimated density of monthly cost of electricity in EUR.

Given the distribution of the MCE, we estimate the model for the quantiles $\tau = 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th}$. Table 7 shows the OLS and quantile regression estimates. In order to test whether all coefficients are zero at different conditional quantiles, we conducted an F-test. For all quantiles we reject the null hypothesis of all coefficients together being zero.

In general the results are consistent and robust, respecting the expected sign. There are no changes in inter-quantile signs, but only in levels of significance and intensity. The effect of the following variables *AGE, NPERSONS*, *STANDBY* and *AC* are consistently positive and statistically significant throughout the whole conditional distribution of the MCE. Therefore, these variables are correlated with high levels of electricity consumption.

Despite the robustness of the results, for some variables the magnitude of the effects varies in response to the level of electricity costs. For other variables, such as *WATERHEATER*, the effect is not statistically significant for all quantiles. We therefore tested the stability of the coefficients for all quantiles by using a global F test. The null hypothesis of jointly coefficient equality at different conditional quantiles was rejected, for a significance level of 1% (Table 8). This suggests that the methodology of quantile regression is appropriate in explaining the MCE of electricity consumption. In addition, we test the stability of each individual coefficient, using a test of equality of the coefficients for each variable. We reject the null hypothesis of equality of the coefficients at different conditional quantiles for the following variables: *NPERSONS, DETACHEDHOUSE, STANDBY, WATERHEATER* and *ELECTRICOOKER*.

Table 7. Household electricity cost: Benchmark OLS vs Quantile Regressions, and expected sign.

Dependent variable – *Monthly cost of electricity (MCE)*

Independent variables	OLS	Quantiles 10%	25%	50%	75%	90%	*Exp. Sign*
AGE	0.34*** (0.05)	0.22*** (0.05)	0.28*** (0.04)	0.39*** (0.07)	0.43*** (0.08)	0.38*** (0.13)	-
RATE	4.98*** (1.18)	3.46*** (0.95)	3.51*** (0.81)	4.44*** (1.01)	3.46** (1.57)	n.s.	+\-
INCOME	1.16*** (0.41)	0.63* (0.33)	0.72** (0.32)	0.75** (0.38)	1.39** (0.54)	2.31** (1.03)	+
NPERSONS	5.03*** (0.52)	3.29*** (0.44)	4.06*** (0.40)	5.23*** (0.53)	6.61*** (0.77)	6.19*** (1.34)	+
HOUSESIZE	0.83*** (0.30)	*n.s.*	0.55*** (0.18)	0.68** (0.27)	0.487 (0.40)	n.s.	+
DETACHED HOUSE	4.61** (2.20)	*n.s.*	*n.s.*	*n.s.*	*n.s.*	*n.s.*	+\-
APARTMENT	-7.46*** (2.14)	-7.40*** (2.11)	-6.66*** (1.28)	-5.22** (2.15)	-9.44*** (3.04)	*n.s.*	+\-
STANDBY	5.49*** (1.17)	3.48*** (0.94)	3.89*** (0.82)	5.08*** (1.12)	8.33*** (1.47)	7.31** (2.96)	+
WASHMACHINE	*n.s.*	1.94*** (0.65)	1.93*** (0.64)	2.21*** (0.76)	2.12** (1.06)	n.s.	+
AC	7.30*** (1.41)	3.79*** (1.17)	4.68*** (1.15)	7.17*** (1.69)	8.24*** (1.96)	9.98*** (3.80)	+
WATERHEATER	15.36*** (1.89)	*n.s.*	6.53*** (2.24)	14.08*** (2.92)	20.66*** (3.88)	40.12*** (10.09)	+
EFFIC CONSUMER	-6.69*** (1.19)	-2.92*** (1.04)	-4.39*** (0.85)	-5.18*** (1.09)	-5.09*** (1.66)	-11.84*** (3.79)	-
ELECTRICOOKER	3.99*** (1.18)	n.s.	n.s.	4.34*** (0.98)	6.28*** (1.51)	*n.s.*	+
CONS	9.08** (4.18)	n.s.	*n.s.*	n.s.	n.s.	31.08*** (11.89)	
N	2156	2156	2156	2156	2156	2156	
R^2/*Pseudo*R^2	0.26	0.12	0.16	0.17	0.21	0.2	
F-test	59.8	24.19	54.03	52.69	56.89	27.06	
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

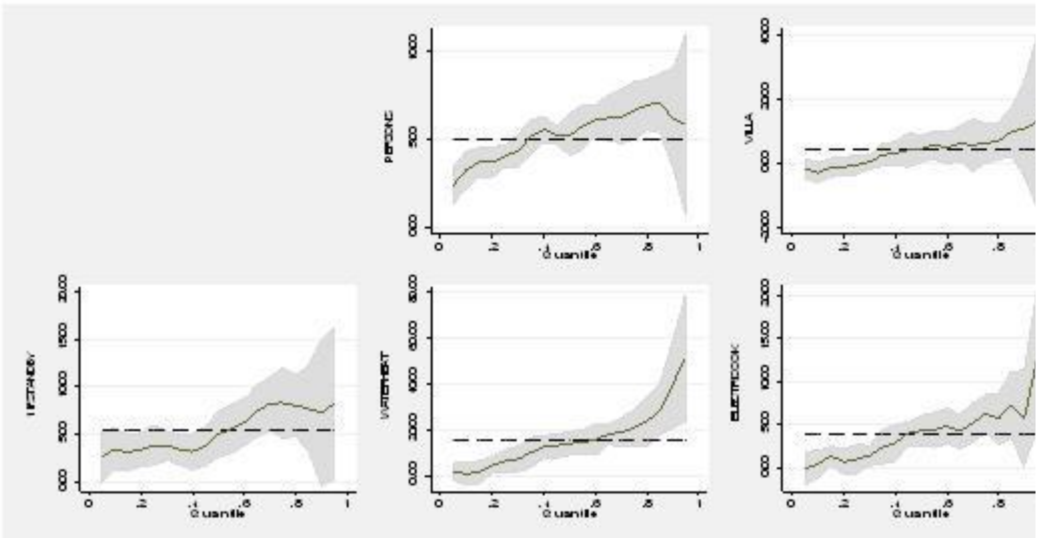
Table 7 Notes: ***, **, denote significance at 1, and 5 significance levels, respectively; Bootstrapped standard errors are reported in brackets; OLS – Ordinary Least Squares; Quantile regression results are based upon 1000 bootstrapping repetitions. "n.s".: denote not significant.

Table 8. Tests of equality of the coefficients at different conditional quantiles.

	AGE	*RATE*	*INCOME*	*N PERSONS*	*HOUSE SIZE*
F-test	1.74	0.4	0.82	5.1***	0.29
	DETACHEDHOUSE	*APARTMENT*	*STANDBY*	*WASHMACHINE*	*AC*
F-test	2.24*	0.79	2.65**	0.35	1.52
	WATERHEATER	*EFFICCONSUMER*	*ELECTRICOOKER*	*ALL*	
F-test	7.75***	1.75	5.01***	5.64***	

Table 8 Notes: AME – Average marginal effect; ***, **, *, denote significance at 1, 5 and 10% significance levels, respectively.

In Figure 4 we present the coefficients and the respective confidence intervals for variables whose stability test reveals different coefficients among quantiles.



Notes: The dashed line represents the OLS parameter estimate. The dark shaded area represents the 95% confidence interval for the quantile regression parameter estimates.

Figure 4: OLS and quantile regression coefficients for each regressor, as τ varies from 0 to 1.

The option for TOU rates influences MCE positively. This result is consistent for all quantiles, with the exception of the quantile $\tau = 90^{th}$, where the effect is not statistically significant. The magnitude of this effect is relatively similar, except for the quantile $\tau = 50^{th}$, where it is higher.

As expected, the effect of income leading to consumption is verified, as shown by Matsukawa (2004) and Abrahamse and Steg (2009). This effect is consistent for all quantiles and the magnitude is increasing. The higher the income is, the greater the incentive for higher consumption of electricity. Variable *NPERSONS* contributes positively to the MCE (Yoo *et al.*, 2007), but this effect loses strength in the last quantile. Unlike Abrahamse and Steg (2009), *AGE* is statistically significant and influences the MCE positively. This result is consistent across all the quantiles, but the magnitude of that effect is small.

The coefficient of the variable *WATERHEATER* is near zero for the lowest quantiles, increasing its effect for higher levels of MCE. In contrast, Figure 4 shows that for the variable *STANDBY* the coefficient is positive for the interval length of τ. Its effect is roughly constant in the first half of the distribution, but the magnitude of that effect is much higher for the second half of the conditional distribution.

High temperature washing helps explain the MCE until the quantile $\tau = 75^{th}$, but afterwards this effect vanishes and loses the power to explain higher costs of electricity. The use of *AC* is statistically significant for all quantiles. Its effect is consistent, positive and has the expected sign. The same result is obtained for the variable *ELECTRICOOKER*.

When we test for the effect of the knowledge and environmental factor, we find that when consumers consider themselves to be efficient consumers, it contributes to reducing their electricity bill. This effect is consistent and statistically significant at a level of significance of 1% for the entire distribution.

5. DISCUSSION

The approach of collecting primary data followed in this study proved to be a useful instrument in studying the decision about electricity rates. Indeed, the flexibility and reliability of the data collected allowed us to proceed to the estimation of different linked models in order to achieve a more complete picture about the rate decision. The estimated models reveal good econometric properties and their results prove to be robust.

Consumers' choice of rate is driven by socioeconomic, behavioral, knowledge and environmental factors. The socioeconomic factor, including variables such as income, the MCE and the percentage of people aged under 18 in the household contribute positively to the choice of the TOU rates, whereas a low level of education has a negative influence. Low levels of education tend to have greater preference for flat rates. These consumers do not have the incentive to decrease their consumption during peak hours, or in doing so, they fail to benefit from this, because they do not have a rate that allows them to make savings in off-peak periods. The effect of university level is not statistically significant, which does not allow us to confirm the results of Faruqui and Sergici (2010).

The highest level of income encourages the choice for differentiated rates, such as in Ek and Söderholm (2008). Looking at the family of quantiles, an increase in income leads to both higher consumption and higher electricity costs. When compared to consumers at the lowest income level, consumers with very high monthly incomes have a 0.14 greater probability of choosing the TOU rates. Those consumers with very high income have a 0.12 greater probability of saving.

The marginal effect of the MCE in the choice of TOU rates appears to be small and is lower than expected (0.002). Consequently, a detailed analysis of the determinants of MCE, testing it for different levels of cost by using quantile regression, is appropriate. Results prove that the option for differentiated rates positively influences the monthly cost. There may be two simultaneous effects for this result: i) the effect that by having differentiated prices for electricity, consumers are able to save on the bill during off-peak periods; and ii) the effect that consumption in peak-periods is more expensive, leading at the same time to increased use of electricity through the "illusion" of lower average price. This result suggests the predominance of the second effect, i.e., the option for TOU rates increases electricity consumption. The latter evidence may be a consequence of the real increase in electricity consumption. For households with a very high MCE, the effect of differentiated rates on the monthly bill is not statistically significant.

The house characteristics factor is important, not only in explaining the choice of rate, but also in understanding the MCE. Houses with a larger number of appliances are more likely to choose TOU rates. We emphasize the use of *AC*. Its use increases the probability of joining a rate with differentiated prices by 0.09. Consumers that are able to change the use of *AC* towards off-peak periods have a 0.58 higher probability of opting for this rate. Testing the effect of *AC* on consumption, as done by Faruqui and George (2005), we observe that the magnitude of its effect is greater for higher electricity bills. The same conclusion is drawn from the use of electricity for water heating. It contributes to a significant part of the MCE, particularly for large levels of consumption. However, this effect is not statistically significant for the initial quantiles of the distribution, a result which may not be surprising. In general, water heating systems require high electricity consumption and, therefore, a low MCE cannot be explained by this variable. This result reinforces the idea of the robustness of the model and appropriateness of the quantile approach.

The use of efficient appliances stimulates the choice of the TOU rates. The higher price of electricity at peak periods is minimized by the more efficient consumption of these devices. Income significance suggests that consumers with lower incomes have more difficulty in purchasing efficient appliances.

The effect of house size on the MCE is positive and statistically significant for the quantiles $\tau = 25^{th}, 50^{th}$. For the first quantile, the reason for non-significance could be explained. Regardless of the area in square meters of the place of consumption, there are fixed costs such as the "voltage charge". At the top of the distribution, the effect of this variable (*HOUSESIZE*) is not statistically significant. This may be due to the reasonable limit for the size of a house. On the other hand, the size itself and its associated costs (such as indoor or outdoor lighting) do not help to justify higher electricity consumption.

In fact, the type of housing has different effects. When compared to a semi-detached house, an apartment contributes to a reduction in the MCE. This effect is consistent for all quantiles. An apartment does not imply outgoings such as outdoor lighting, gate mechanisms and costs associated with outside space maintenance. This effect follows a quadratic function pattern, with the minimum for the average cost of consumption. As expected, the intensity of this effect is greater at the high end of the distribution.

Overall, the variables from the behavioral factor are statistically significant in explaining the choice of rates. Consumption mostly occurring in off-peak periods increases the probability of choosing TOU rates by 0.31, and this result is in line with what was expected. This fact could be compatible with a reduction in peak loads, even though the possible reduction in peak demand might not be testable upon our database. Consumers who consider peak periods more relevant for consumption reduce their aptitude to join the TOU rates. The price during this period is slightly higher than in the flat rate. The use of a cooker or hot plate reduces the propensity for TOU rates, since the use of such equipment occurs mainly at peak times of lunch and dinner, making it difficult to change routines and to achieve the desired switching effect.

Leaving appliances on standby increases the MCE and this effect is consistent throughout the entire conditional distribution. The magnitude of this effect is large and it is greater at the top of the distribution, i.e., for consumers who consume more electricity. This is the variable that shows a greater impact on the rising cost of electricity, but at the same time it is one of the variables that consumers can most easily influence, by simply unplugging their appliances. Changing routines in the periods of consumption, from peak to off-peak, is important in increasing the opportunities for saving. Consumers able to change consumption routines allow an increase of about 33% in the probability of cost savings. When a consumer changes the rate to TOU rates (which happened in 66% of the cases) and can change their consumption routines, then the probability of saving increases by 28%.

Results strongly support that the policy design must be focused on both: (1) efficiency; and (2) consumer knowledge about the electricity market. In fact, regulatory policies cannot be focused only on the promotion of efficiency. It is crucial to ensure that consumers fully understand the costs of providing uninterrupted electricity supply, both in the peak and off-peak periods. It requires effort to discipline the demand throughout the day. Consumption in peak periods needs to be allocated to off-peak periods in order to make use of electricity's optimal installed capacity, with lower generation cost. Therefore, policy makers should encourage the switch in consumption to off-peak periods in order to change consumer routines. This could be done, for instance, through new ways of delivering information on pricing options, highlighting TOU rate advantages. This has already been done via the electricity bill, but this may not be the best way to attract consumer attention, these campaigns may not be in line with the desired effect. Indeed, it is not through the monthly electricity bill they have to pay that they will be persuaded to switch their rates. Another policy measure could be to make TOU rates compulsory for consumers with suitable profiles for making the switch. At the same time, policy makers and practitioners should develop a framework with a progressive price in peak-period, and a regressive price in off-peak, according to levels of consumption. Policy makers can also manipulate significant factors such as the level of efficiency in appliances. They could make it compulsory for stores to accept old, inefficient appliances in part-exchange for a new one with the highest level of efficiency. On the production side, policy should promote competition among the players, namely by reducing entry barriers and opening the network to new entrant players. Producers that promote smooth electricity demand should be rewarded with tax breaks.

Awareness campaigns could be targeted at specific types of household, such as higher-income households. These consumers have higher electricity consumption, mainly not due to essential activities such as cooking. Consequently, they would be more likely to switch consumption towards off-peak. In the same way, campaigns focused on kids should be promoted by regulators, possibly early on in school life. Indeed, kids make extensive use of electronic appliances such as electronic games, computers, and televisions. Therefore, they should be advised to use sockets with a switch (power strips) that allow electrical appliances to be turned off and avoids leaving them on standby.

This study reveals some limitations, mainly as a consequence of the approach followed. Indeed, the collection of primary data through questionnaires does not allow us to quantify the possible reduction in peak consumptions, nor does it study the optimal peak period length. Further research is therefore needed, which can combine the collection of data, as we did, with data from consumption meters. Both reveal their own advantages and disadvantages. Unlike the data from consumption meters, the questionnaires enable consumer perception to be recognized and information to be collected on variables that otherwise would not be available, which are both precious to the definition of policies.

6. Conclusion

This study adds to the literature about electricity pricing, contributing to the debate on the peak-load pricing problem. Primary data was gathered from the Portuguese household electricity market through questionnaires. They allow data to be collected and several consumer characteristics to be tested, which proved to be important in the choice of electricity rates. We identify both the main drivers of the choice of rate and the consumer profile allowing savings in the change of rate. Therefore, the Monthly Cost of Electricity is analyzed by level of consumption.

Consumers' choice of rate is driven by socioeconomic, behavioral, knowledge and environmental factors. Housing characteristics also influence consumer choice. A low level of education discourages the option for differentiated rates, while the number of people in the household, the importance of consumption held in off-peak periods and the household income encourage consumers to opt for differentiated rates. It was further observed that the fact that a consumer has knowledge about how the electricity market functions has a positive influence on the choice of TOU rates. Knowledge and adjusting daily routines in order to adjust to the market could increase the potential savings in the monthly cost of electricity. Regulation plays a crucial role in deepening the interrelationship between consumer behavior and electricity market supply, by inducing the switch to consumption during periods with excessive capacity to generate electricity.

The quantile technique is used because the marginal effect of the variable cost pricing on the determinants of choice is lower than expected. It was found that the effect of water heating is statistically significant and of larger magnitude in the upper quantiles. The same applies to the use of AC. It appears that the effects of the physical characteristics of the place of consumption, in particular the size of the housing, only have a statistically significant effect on the intermediate monthly costs. Regarding the type of housing, compared to a semi-detached house, an apartment contributes to a decrease in the monthly cost of electricity, which is a consistent effect for all quantiles.

These results lead to some questions for further research. What should the role of regulatory authorities be in changing consumer routines? Will the new features of electricity demand, such as sustainable mobility based on electric vehicles, require new pricing policies in order to deal with rationalization of the installed electricity capacity?

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APPENDIX

Table A1. Correlation matricx for the variables (Model III)

	Rate	Income	Cost	Persons under 18	Sec School	University	Appliances	AC	Apartment	Detached House	Electric Oven	Electri-Cooker	Effic Appliances	Weekend Peak	Morning	Afternoon	Dinner	Off-Peak	Standby	Effic Consumer	Cost Prod	Effic Bulb	Stop Prod
Rate	1.00																						
Income	0.17	1.00																					
Cost	0.16	0.19	1.00																				
Persons under 18	0.17	0.17	0.21	1.00																			
Sec School	0.02	-0.19	-0.01	0.07	1.00																		
University	0.05	0.33	0.00	-0.01	-0.71	1.00																	
Appliacnes	0.23	0.30	0.39	0.25	0.01	0.03	1.00																
AC	0.13	0.10	0.15	0.06	0.00	0.04	0.29	1.00															
Apartment	-0.04	-0.03	-0.29	-0.12	-0.03	0.15	-0.25	-0.06	1.00														
Detached House	0.07	0.06	0.07	0.09	0.00	0.02	0.09	0.04	-0.37	1.00													
Electric Oven	0.13	0.16	0.10	0.13	0.03	0.04	0.37	0.08	-0.05	0.06	1.00												
Electri-Cooker	0.04	0.09	0.07	0.00	-0.04	0.06	0.24	0.04	0.05	0.02	0.17	1.00											
EfficAppliances	0.06	0.06	-0.04	0.00	-0.05	0.10	0.06	0.04	0.02	-0.05	0.06	-0.03	1.00										
Weekend Peak	-0.10	-0.01	-0.01	0.03	0.00	0.00	-0.02	-0.01	0.02	-0.01	-0.02	-0.05	0.00	1.00									
Morning	-0.08	0.00	0.08	-0.03	-0.03	0.00	0.01	-0.01	-0.03	-0.03	0.00	0.04	0.01	0.11	1.00								
Afternoon	-0.07	-0.08	0.05	-0.04	0.00	-0.06	0.02	-0.02	0.02	-0.04	-0.02	0.05	-0.04	0.01	0.19	1.00							
Dinner	-0.21	0.00	-0.06	0.02	0.02	-0.01	-0.01	-0.02	0.02	-0.03	0.02	0.00	0.00	0.37	0.03	-0.11	1.00						
Off-Peak	0.32	0.05	0.05	-0.01	-0.01	0.04	0.06	0.05	0.05	0.03	0.01	0.02	0.01	-0.08	-0.06	-0.10	-0.42	1.00					
Standby	0.03	0.08	0.15	0.03	0.00	-0.02	0.16	0.09	-0.01	0.00	0.03	0.04	-0.08	-0.03	0.04	0.01	0.01	0.02	1.00				
Effic Consumer	0.06	-0.03	-0.16	-0.02	0.01	0.02	-0.08	-0.04	0.01	0.02	0.01	-0.04	0.18	-0.03	-0.01	-0.03	-0.08	0.03	-0.24	1.00			
Cost Prod	0.11	0.10	0.04	0.02	-0.03	0.07	0.07	0.02	-0.01	0.01	0.06	-0.04	0.06	0.01	0.00	-0.01	-0.03	0.04	-0.04	0.07	1.00		
Effic Bulb	0.04	0.07	0.05	0.01	-0.01	0.01	0.10	0.03	-0.07	-0.01	0.00	-0.08	0.09	0.04	0.03	-0.03	-0.01	0.05	-0.05	0.06	0.05	1.00	
Stop Prod	0.00	0.12	-0.02	0.00	-0.06	0.06	0.04	0.03	-0.04	-0.03	0.03	-0.03	0.11	0.01	0.00	-0.01	-0.06	0.04	-0.06	0.11	0.22	0.10	1.00

Table A2. Correlation matrix for the variables (Model V)

	SAVE	*RATE*	*INCOME*	*PERSONS*	*WASHMACHINE*	*AC*	*APARTMENT*	*DETACHEDHOUSE*	*ELECTRICOVEN*	*ELECTRICOOKER*	*WATERHEATER*	*GARDEN*	*OFF-PEAK*	*CONSROUTINES*	*EFFICCONSUMER*	*RENSYSTEMS*	*INFOSUM*
SAVE	1.00																
RATE	0.52	1.00															
INCOME	0.15	0.15	1.00														
PERSONS	0.10	0.11	0.17	1.00													
WASH MACHINE	0.05	0.06	0.05	0.10	1.00												
AC	0.02	0.01	0.11	0.02	-0.02	1.00											
APARTMENT	-0.06	-0.05	-0.04	-0.22	-0.02	-0.02	1.00										
DETACHED HOUSE	0.03	0.08	0.03	0.08	0.03	0.01	-0.37	1.00									
ELECTRIC OVEN	0.08	0.06	0.12	0.06	-0.01	0.05	-0.03	0.01	1.00								
ELECTRI-COOKER	-0.05	-0.01	0.10	-0.04	0.02	0.06	0.04	0.00	0.15	1.00							
WATER HEATER	-0.03	-0.01	-0.02	0.13	-0.01	0.03	-0.13	-0.01	0.00	0.07	1.00						
GARDEN	0.10	0.04	0.09	0.15	-0.01	0.00	-0.77	0.20	0.05	0.02	0.09	1.00					
OFF-PEAK	0.17	0.20	0.03	0.02	0.03	0.02	0.03	0.04	-0.02	0.01	0.03	0.00	1.00				
CONS ROUTINES	0.37	0.30	0.04	-0.02	-0.01	-0.01	-0.02	0.06	-0.02	-0.07	-0.03	0.02	0.11	1.00			
EFFIC CONSUMER	0.11	0.06	-0.05	-0.09	-0.09	0.00	-0.06	0.05	0.05	0.00	-0.01	0.02	0.02	0.16	1.00		
RENSYSTEMS	0.02	-0.01	0.09	0.05	0.00	0.03	-0.33	0.04	0.09	0.02	0.10	0.34	0.01	0.07	0.13	1.00	
INFOSUM	0.09	0.01	0.10	0.01	-0.01	0.03	-0.02	-0.05	0.02	-0.01	-0.03	-0.03	0.05	0.11	0.13	0.03	1.00

Table A3. Correlation matrix for the variables (Model of table 7)

	COST	*AGE*	*RATE*	*INCOME*	*NPERSONS*	*HOUSESIZE*	*DETACHEDHOUSE*	*APARTMENT*	*STANDBY*	*WASHMACHINE*	*AC*	*WATERHEATER*	*EFFICICONSUMER*	*ELECTRICOOKER*
COST	1.00													
AGE	0.19	1.00												
RATE	0.16	0.05	1.00											
INCOME	0.19	0.18	0.17	1.00										
NPERSONS	0.32	0.10	0.13	0.17	1.00									
HOUSESIZE	0.24	0.17	0.17	0.37	0.20	1.00								
DETACHEDHOUSE	0.07	0.03	0.05	0.09	0.07	0.14	1.00							
APARTMENT	-0.30	-0.14	-0.04	-0.04	-0.28	-0.34	-0.37	1.00						
STANDBY	0.15	-0.03	0.02	0.10	0.06	0.03	0.01	0.00	1.00					
WASHMACHINE	0.09	0.04	0.07	0.07	0.10	0.07	0.05	0.00	0.06	1.00				
AC	0.16	0.05	0.12	0.10	0.04	0.09	0.05	-0.06	0.07	0.02	1.00			
WATERHEATER	0.21	0.04	0.06	0.00	0.07	0.03	-0.01	-0.12	0.02	-0.01	0.03	1.00		
EFFICICONSUMER	-0.16	-0.02	0.06	-0.02	-0.09	-0.03	0.01	0.01	-0.23	-0.09	-0.04	-0.01	1.00	
ELECTRICOOKER	0.08	-0.12	0.05	0.11	0.01	0.06	0.01	0.06	0.04	0.08	0.05	0.07	-0.04	1.00