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DRIVERS OF ELECTRICITY POVERTY IN SPANISH DWELLINGS. A QUANTILE REGRESSION APPROACH

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ABSTRACT

The main objective of this article is to explore the causes of household electricity poverty in Spain from an innovative perspective. Based on evidences of energy inequality across households with different income levels, a quantile regression approach is used to better capture the heterogeneity of determinants of energy poverty across different levels of electricity expenditure. Results illustrate some interesting and counter intuitive findings about the relationship between household income and electricity poverty and the technical sufficiency of quantile regression compared to the blurred results of a standard single coefficient / OLS approach.

Keywords: Electricity poverty,

1. INTRODUCTION

Energy poverty and vulnerability are critical issues. According to current research the problem is extensive and even severe in many countries. Recent data available on the EU survey on Income and Living Conditions estimates that around 11% of the EU population were unable to keep their home adequately warm. In the particular case of Spain, where a long and serious economic crisis have deeply deteriorated living conditions for millions of people, some recent reports have alerted about the extent of this problem (see Tirado et al. 2016) urging politicians and energy companies to take an active role in the debate.

The main objective of this article is to explore the causes of household electricity poverty in Spain, with a special focus in the impact of household income levels in electricity power expenditure.

The standard analyses of electricity consumption for a given country, region or area, frequently use some average household expenditure ratios that do not fairly represent the whole population they attempt to describe. The average value of energy household spending is not of real interest if different levels of energy consumption are caused, affected or reversed by different factors with different intensity. In this context, electricity poverty, understood as an extreme value of energy relative expenditure, deserves a particular attention. Lessons learnt from empirical exercises aimed to explain electricity household consumption as a whole might not be extrapolated to poorest households and will not be of any particular interest when it comes to determine how to tackle electricity poverty at the household level.

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Consequently, the quantile regression emerges as the most suitable technique to perform a fruitful analysis about the explanatory variables of electricity household relative expenditure instead of standard regression. In effect, as will be later shown, estimated coefficients for the main drivers of electric energy household consumption present very different values across different energy relative expenditure quantiles.

The present paper clearly complements the existing literature in this field. Firstly, although there exists a vast literature on the causes of average energy consumption using standard econometrics, a quantile approach is not that common. Additionally, even though the drivers of electricity consumption or saving have received an extensive attention in the economic literature at a cross-country level, there are very few studies specifically related to electricity poverty (or vulnerability) in a developed context and at the household level (see Middlemiss and Gillard, 2015).

Specific attention to household behaviour and causes of electricity poverty for families is crucial from the policy perspective in a moment where debates about different dimensions of economic and social exclusion have gained momentum in the political arena, even in the context of well - developed EU countries. In the age of new technologies and globalization of massive communication, electricity scarcity not only affects basic needs such as heating, freezing food or sanitation, but also hinders access to communication, e-learning activities, e-commerce, …; electricity poverty emerges as a contemporary driver of social inequality.

This article is structured as follows. In the second section, a review of the theoretical and literature background is carried out, highlighting the main variables and estimation techniques previously used in other texts. In the third section, we summarise some of the advantages of the quantile regression approach in the context of the electricity poverty analysis. In the fourth section, a descriptive analysis of the data is conducted. In the fifth section, the results of quantile regression is exposed and discussed ending with a set of main conclusions.

2. DEFINITIONS, THEORETICAL BACKGROUND AND LITERATURE REVIEW

Definition of Energy Poverty/Vulnerability

Day et al. (2016) define Energy Poverty as "*an inability to realise essential capabilities as a direct or indirect result of insufficient access to affordable, reliable and safe energy services, and taking into account available reasonable alternative means of realising these capabilities*". A similar characterisation is used in Bouzarovski and Petrova (2015): *"the inability to attain a socially and materially necessitated level of domestic energy services […] tied to the ineffective operation of the socio-technical pathways that allow for the fulfilment of household energy needs"*. This broad definition could be applied to all socio - economic spectrum and would be valid either for under developed or well - developed countries; in the case of our study, Spain, "insufficient accessibility" should be understood not as a physical barrier, but as a budget constrain.

The term "energy poverty" is then commonly associated with household energy deprivation and commonly used in this sense across EU countries where, in the last years, this problem has gained momentum as part of the political and social debate in a context of spreading inequality. The EU "Third Energy Package" (2014) also uses the term in this sense.

In our paper, we will focus our econometrical analysis on the specific concept of "Electricity Poverty" or "Electricity Vulnerability". Electrical power can be considered the main and default

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source of energy in a household and therefore, the component that better and primarily would capture an energy deprivation household condition. Apart from that reason, we wanted to align our conclusions with public policy issues and, in that sense, electricity poverty has become the public policy standard measure in Spain when it comes to implement aid programs for vulnerable families.

We should admit that the use of "electricity poverty" is explicitly excluding household's energy expenditures for the basic need of heating homes in winter. In order to avoid bias in our analysis, we will always control for substitutive energy expenditures in the household given that, alternative sources of energy extensively used by families in Spain such as natural gas for heating or boiler, may have a clear impact in electricity expenditure. In that sense, including natural gas expenditure as a control variable is also essential in the case of Spain given that temperatures map is quite heterogeneous, to the point that heater devices are almost never used during the whole year in a part of the territory. The Household Budget Survey (HBS) for 2015 shows that more than 33% families have not heating systems at all at their homes. This average percentage varies from 97% in Canary Islands, Ceuta or Melilla, to around 5% in central regions or 50% in southern coastal areas.

UK was pioneer in facing this problem, and from early 1996 established some help mechanisms for people expending in household energy more than a fixed percentage of their total incomes (10%). As pointed out in Day et al. (2016): *"Annual 'excess winter deaths' statistics for the UK show every year a peak in the number of deaths during winter months that run to the tens of thousands […] a fact which is generally attributed to the poor energy efficiency of the UK housing stock, making houses expensive to heat".*

On the other hand, the use of electricity as the pivot variable to identify energy vulnerability is especially suitable for Spain because of the widespread use or air conditioning during the hot Spanish summer. While some authors consider that issues related with cooling households are not essential and should not be included in the "Energy poverty" term, other authors disagree (see Harrison and Popke, 2011 for example). The effects of extremely high temperature in labour conditions, health, and quality of life are obvious, and the access to AC devices should be explicitly considered in terms of "energy poverty".

For the case of France, maybe more similar to the Spanish case (where heating is not always the main problem), the definition of "energy precariousness" is "*a person encountering 'particular difficulties in their accommodation in accessing the necessary energy supply to satisfy basic needs, due to inadequacy of financial resources or of housing conditions"* (De Quero and Lapostolet, 2009).

As a final caveat, it is worth mentioning that the measures of energy vulnerability or scarcity are commonly addressed by computing energy consumption, but we have to realize that people do not directly demand energy itself but the services provided by electricity or other sources. Families demand energy for washing, cooking, lighting, HVAC, mobility … In view of this observation, some authors have proposed a different focus called Services Approach where the adequate satisfaction of these services will rule the definition of "Electricity Poverty". Essentially, this is like measuring income poverty by looking at material deprivation or affordability of some items thought to be indispensable for people to have a satisfactory standard of living. Unfortunately, it is almost impossible to get detailed household data about energy services available at households.

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Measuring electricity poverty: the income effect

There is not a unique consensus definition of how to identify households in energy poverty, but under the idea of *high spending / low-income,* many authors, European countries experts, and the EC itself (EC, 2010) continue to use the ratio of household expenditure on energy as an unbiased description of energy poverty. For the particular case of electricity, a simple way of estimating energy vulnerability of a family is to examine the ratio between average per capita energy expenditure over family income.

$$\frac{Electricity\ Expenditure}{Total\ Revenues(FamilyIncome)} * 100$$

By computing decile's thresholds for this ratio at the national level we can then identify a "at risk of energy poverty household" when the ratio for that household is above 80% or 90% decile threshold (or another similar arbitrary limit such as two times the national median).

Income dynamics are energy expenditure may follow different dynamics and be reactive to different policy measures (Phimister et al. 2015) but the aim of this relative measure is to relate energy poverty with income poverty; the ratio may worsen either if income conditions deteriorate and/or energy expenditure increases (due to changes in prices, temperature or living conditions).

This type of ratio has been criticized because when facing income restrictions, families may adjust their energy expenditure, especially for heating their homes in winter, under the optimum level (Brunner et al. 2012). Even if this is true for some countries and for some types of energy expenditure, the Spanish data for electricity expenditure do not confirm this idea. Data shown in the table below illustrate that, except for poorest households[1], total electricity expenditure is quite inelastic to household income levels, supporting the idea of using this standard ratio as our variable of analysis. In effect, per capita electricity demand is around 369 euros for almost all of the revenue trims.

Per capita yearly electricity expenditure by monthly revenue level

Monthly revenue	Mean	Median	Std. Dev.	Obs.
< 500 euros	344.2473	294.5735	222.4565	966
500-1000 euros	391.3066	340.3448	256.0153	3731
1001-1500 euros	375.3440	322.9200	253.1211	4503
1500-2000 euros	370.9687	317.6848	243.9479	3640
2000-2500 euros	363.8701	311.5983	228.3826	3039
2500-3000 euros	352.2644	306.3529	237.3860	2345
3000-5000 euros	350.2464	300.0000	222.2108	2850
5000-7000 euros	363.5584	313.6333	233.3433	470

[1] There is another exemption for the highest revenue group but this could be considered atypical or anecdotical because only 55 observations (out of a total of 21.735 households) lay in this sample group.

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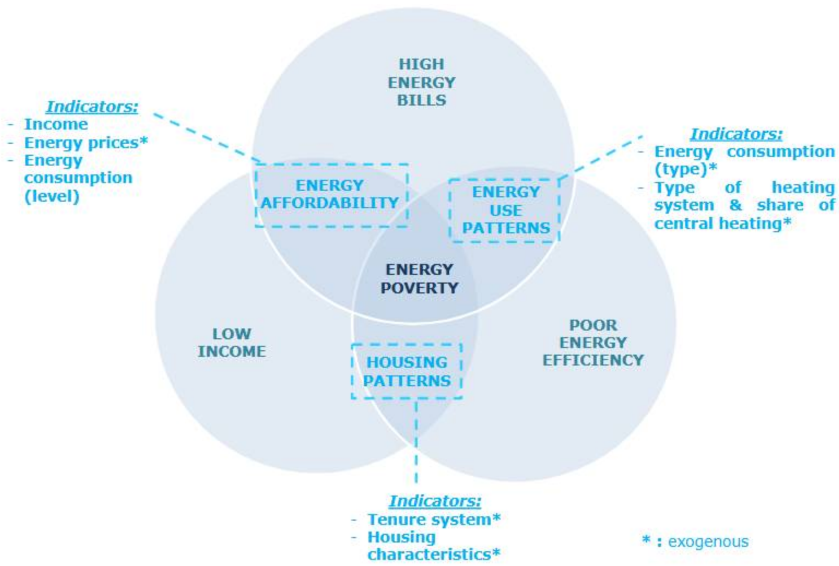
7000-9000 euros	378.5435	326.0500	209.2936	136
> 9000 euros	588.7737	375.0000	676.7883	55
GLOBAL	368.8893	316.6667	243.7883	21735

Source: Own calculations with 2015 data from Household Budget Survey (National Institute of Statistics - INE). OECD house size equivalence was taken to estimate the per capita expenditure.

The reason behind this inelasticity in the Spanish case could be that electricity is used for heating only in a minimum fraction of dwellings, normally located in warm locations; services provided by electricity expenditure are so essential (lighting and plug in devices such as fridge, washing machine, ceramic hubs …) that electrical bill becomes quite difficult to adjust below a certain minimum level. If this hypothesis is true, we can then assume that an increase in the family revenue will not automatically produce an increase in the electricity bill (except for poorest households) but a change in the electricity poverty ratio. It should be remember, at this point, that relationship between income and energy poverty is central in our article: we don't only want to determine the main causes of electricity poverty but to explore differential effects of that factors across different income levels.

Drivers of household electricity poverty

Household energy poverty usually appears as a consequence of a triad of high energy prices, low income and poor energy efficiency of the residence.



Source: Pye et al. (2015)

Different variables for these three different areas and intersections are commonly used in the literature. Following this approach, we will also use a four groups classification of explanatory variables that could be related to electricity consumption:

Environment /Geographical variables	Dwelling / Infrastructural variables
Neighbourhood density, heating and cooling degree-days, Climate, Urban structure…	Geometry, envelope fabric, **equipment and appliances, indoor temperatures, heating system**, equipment use, **building age…**

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Electricity Usage/Behavioural variables	Family status
Gender, Nationality, Professional occupation, **Educational skills, household size and family age structure…**	**Ownership status (tenure), Housing type**, **Family income**, occupancy schedules…

In a recent study, Middlemiss and Gillard (2015) carried out an interview among "vulnerable families" in the UK. Based in their qualitative assessment, they found out six categories of variables deeply related with this situation: quality of dwelling fabric, energy costs and supply issues, stability of household income, tenancy relations, social relations within the household and outside, and ill health. The main contribution of this paper, coming from its qualitative interview, is related with their findings in term of private and public efficiency of the strategies to cope with vulnerability.

The connection with electricity consumption is almost obvious for most of the variables included in the previous table.

The geographical context is normally a clear determinant in electricity consumption. In the case of Spain, regional disparities are relevant in terms of climate conditions, but considering that electricity is not commonly used for heating (only around 14% of dwellings according to the Families Budget Survey, 2018) the impact of regional climate may not be very relevant. Nevertheless, regional average electricity consumption shows large heterogeneity across Spain (see table below) suggesting the need of adding a regional dummy indicator as a control variable. This variable would account for other climate conditions such as sunlight hours and, at the same time, would control for other sources of unobserved regional heterogeneity that may bias the rest of coefficients.

Regional electricty consumption per dwelling (MW)

	Mean	**Percentile 25**	**Median**	**Percentile 75**	**Interquantile % of difference**[2]
Andalucía	715	420	623	894	76,0%
Aragón	668	399	570	789	68,5%
Asturias	584	344	491	709	74,4%
Baleares	865	480	736	1100	84,1%
Canarias	584	336	509	720	75,5%
Cantabria	598	360	518	727	70,8%
Castilla y León	576	340	493	708	74,6%
Castilla – La Mancha	755	404	606	900	81,7%
Cataluña	659	366	544	816	82,8%
Valencia	701	406	600	882	79,4%
Extremadura	681	371	577	840	81,4%
Galicia	630	360	537	791	80,2%
Madrid	653	384	557	804	75,4%
Murcia	752	420	660	960	81,8%
Navarra	581	365	512	720	69,3%
País Vasco	583	355	500	720	72,9%
La Rioja	552	354	490	692	69,0%
Ceuta	452	282	408	581	73,2%

[2] Difference between the 75% and 25% percentiles divided by the median.

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	Mean	Percentile 25	Median	Percentile 75	Interquantile % of difference[2]
Melilla	660	420	600	780	60,0%

Source: Household Budget Survey 2012 and 2016 (INE) and own calculations

The variables related to dwelling characteristics and household equipment are of great importance for obvious reasons but, unfortunately, for most of the countries, it is very difficult or impossible to gather homogeneous micro data information at a national level. For the Spanish case, we neither have this type of data, at least for those households whose electricity expending we have explored with the Household Budget Survey (HBS). Our proposal is, at least, to control for building age (disposable at the level of the HBS) as a proxy of several variables related to dwelling infrastructure. We expect that an older dwelling will be associated with a bigger electricity consumption because of a poorer energy efficiency (Santin et al. (2009) Rehdanz (2007) and Vaage (2000)). For the size and type of electrical appliances, family income will probably work as a proxy variable.

In the group of family status, household size and family composition have been frequently pointed out as very important variables to define energy demand (see Estiri, 2014 or Kelly, 2011). Some authors have also pointed out an indeterminate effect of tenure in dwellings consumption. Sardianou (2008) or Vaage (2000) found that owner tend to consume more energy than tenants. Conversely, Rehdanz (2007) or Meier and Rehdanz (2010) found negative or no significant effect.

In the group of usage/behavioural variables, some characteristics about the educational skills, gender, nationality and household age structure are englobed. Using similar sets of variables, You and Chen (2013) and Belaid and Garcia (2015) emphasizes the crucial role of personal behaviours in the final electricity consumption. Based in some previous findings (see Summerfield et al, 2010), these authors verify that household's energy consumption can vary up to three times because of behavioural patterns even sharing similar building characteristics.

About electricity price, 95% of consumers pay the so-called "last resource tariff" in Spain so, in our view, it is not crucial to have a measure about prices using a cross section analysis.

3. METHODOLOGY

There is a vast literature in estimating the electricity consumption or saving behaviour at the dwelling level but it is not so common to find specific studies about "electricity poverty" or "electricity vulnerability".

The technical or statistical approach used to analyse energy or electricity consumption drivers has been very heterogeneous (see Yue et Al, 2013). Swan and Urgusal (2009) propose a simple classification of different techniques depending on the initial approach defined by researchers: top-bottom or bottom-up. In both cases, time series analysis of electricity demand is more frequent than cross-sectional data analysis.

From the top-down approach, the macroeconomic optic rules the behaviour of the individual typical consumption. From the bottom-up approach, available temporal and cross-section microdata allows more or less accurate predictions of short-term future consumptions by family units. Concentring in the second one as it is the selected in this paper, frequently authors

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distinguishes among statistical and engineering techniques. In the first case, they highlight regression, conditional demand analysis, and neural networks as the preferred method to estimate the relations among selected explanatory variables and electricity demand. In the second one, they point out the population distribution, archetype and sampling methods as the most common techniques.

In a recent article, Fumo and Biswas (2015) depict the use of traditional regression analysis in this research area, quite common during last years because of much more micro residential data on energy habits and consumption available. Technological advances for an accurate measurement of electricity consumption per hour partially explains the re-adoption of regression to understand family patterns of spending; even by using simple models we get a reasonable accuracy in short-term forecasting.

Although traditional regression has been the preferred technique to estimate electricity demand, some authors pointed out the difficulties of this approach in capturing the marginal effects at the individual level. The huge and very informative heterogeneity observed in micro data is somewhat ignored when using the traditional regression than mainly focuses the average behaviour (see Kaza, 2010).

Additionally, a rigid standard regression would normally fail in the presence of heterocesdasticity, frequent outliers, non-normality, non-linearity, non-permanent coefficients for each explanatory variable depending on the relative level of the final electricity consumption.

As is well known, the basic linear regression model rests under the assumptions of Gauss-Markov compliance to ensure that the obtained estimators are linear, unbiased, optimal and consistent. These conditions impose on the model the hypotheses of linearity of the mathematical relation; null mean, homoscedasticity and no autocorrelation in the perturbations and strict exogeneity (random perturbations will not be conditioned by the values of the explanatory variables). At the same time, the credible maximum estimate will coincide with the Ordinary Least Square (OLS) estimator only if the random perturbations are distributed as a normal, with zero mean and constant variance.

The proposed framework for making estimates using ordinary least squares in the regression to the usual mean is frequently violated. In the first place, maintaining the same proportionality of response of the explained variable to changes in the explanatory (linearity) does not seem congruent on several occasions. In the subject dealt with in this research, it seems reasonable to think that the response on electricity consumption to, for example, a very high income situation cannot be the same as to a very low income. The economic effort in the first deciles of consumption before a low income is surely much greater than the same in the case of a high income. In other words, covering a minimum electricity cost for low incomes will require a great deal of effort, while it will be practically irrelevant for high incomes.

Second, the hypothesis of homoscedasticity (variance of constant random disturbance throughout the sample) is also frequently violated in the case we are working on. It seems sensible to think that the determinants not expressly included among the explanatory variables, and therefore included in the random disturbance, will be very different if we consider low consumption levels than large consumers.

Thirdly, the hypothesis of normality of resids is violated both empirically (when regressions of cases such as the present are made using ordinary least squares) and theoretically. Again, it is difficult to think of homogeneous behaviour in a highly modulable consumption variable when

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dealing with low and high consumers. Maintaining the mean as the most probable value is not data driven.

Quantile regression effectively treats the previously defined limitations by relaxing the assumption of normality, although, essentially, its main characteristic consists of providing a different estimate of the coefficients for the different quantiles considered for the variable under study. In our context, this procedure makes full sense if we have reason to believe that the importance of the explanatory variables of electricity consumption is not homogeneous for the different levels of consumption. In this sense, quantile regression emerges as the most appropriate technique to have an accurate and impartial estimate of the effect of explanatory variables for the most vulnerable households.

In the following section, a brief summary of the principles governing quantile regression is provided.

In order to circumvent the lack of adaptation and to take advantage of micro data information we will use Quantile Regression as a better analytical framework for coefficients' estimation.

The quantile regression deals effectively with the limitations previously defined relaxing the assumption of normality but, essentially, its main feature consists in providing different estimation of coefficients for the different quantiles considered for the variable under study. IN our context, this procedure makes complete sense if we have reasons to believe that the importance of the explanatory variables of electricity consumption is not homogeneous for different levels of consumption. In this sense, quantile regression emerges as the most suitable technique to have an accurate and unbiased estimation of the effect of explanatory variables for most vulnerables households.

Briefly, we will summarize the quantile regression method in the next section.

4. NOTE IN QUANTILE REGRESSION ASUMPTIONS

Shortly, alternatively to the common OLS estimator based on the mean, the quantile regression estimator is based on the same idea, but taking into account the median (or other selected quantile) and minimizing the sum of absolute resids (instead of the sum of square resids).

$$\sum_i |y_i - median|$$

As Koenker and Basset (1978) demonstrated, in the above equation, the equal weight of both the left and right sides of the endogenous variable produces an accurate estimate of the median. Therefore, by weighting each tail of the distribution by the desired quantile and minimizing the previous function, we can find the specific coefficients for this any other quantum (call it τ%):

$$\sum_i \rho_\tau |y_i - q|$$

Where the weighted factor (ρ_τ):

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$$\rho_\tau(x) = \begin{Bmatrix} -x.(1-\tau) & x < 0 \\ x.\tau & x \geq 0 \end{Bmatrix}$$

In the traditional regression for the mean, the estimated value of the endogenous corresponds to the mean hope conditioned by the set of variables and the explanatory parameters-variables Xβ, resulting in:

$$\hat{y} = \mu = E(y|X\hat{\beta})$$

Similarly, we can write this expression for quantiles in the following way:

$$\hat{y} = q = quant(y|X\hat{\beta}_\tau)$$

Therefore, we could estimate the coefficients for each quantum using the following expression:

$$min \sum_i \rho_\tau |y_i - X\hat{\beta}_\tau|$$

This expression could be rewritten as follows:

$$min \left\{ \sum_{Y_i \geq X_i\beta} \rho_\tau |y_i - X\hat{\beta}_\tau| + \sum_{Y_i < X_i\beta} (1-\rho_\tau)|y_i - X\hat{\beta}_\tau| \right\}$$

Where is straightforward to observe the process underlying the quantum estimation method. Specifically, it would be a weighted estimation through linear optimization algorithms in which the observations included in the quantile of interest are weighted higher than those that are outside that quantum. Seen differently, an asymmetric weighting would be given to positive and negative errors, allowing the estimation of different parameters for each quantile chosen.

It is also interesting to point out here how the use of absolute values versus the square of traditional regression minimizes the effect of outliers on the parameters estimated by treating them linearly and not "exaggerated" through the square power involved in the OLS estimation.

Another additional advantage of this estimation method is that it allows us to avoid the so-called "Heckman selection bias" (Heckman, 1976) present in many investigations that choose to make multiple estimates using ordinary least squares and plotting the sample by deciles. This sample trimming produces biased parameters, invalidating their later applicability. In the quantile regression, the total sample is always used, although conveniently weighted.

Although Koenker and Bassett (1978) formulated quantile regression in the late 1970s, this technique has not been used very often until recent times. In the past, two issues inhibited its use: the complex minimization algorithm to obtain the coefficients and the weakness of the confidence intervals of the estimated coefficients in the absence of the assumption of normality in random disturbances. Currently, the exponential growth in computational capacity and the

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ease of avoiding confidence interval problems through the use of bootstrapping techniques have produced an excellent scenario for using this technique without difficulties.

Several authors have addressed the problem of estimating the coefficients confidence intervals in the framework of this “semi-parametric” regression. Hoenker and Hallock (2001) proposed up to five different alternatives for what are known as range inversion intervals. Powell's (1989) estimator, known as the "Sandwich method", determines the covariance of the estimators based on independent and identically distributed errors through sample randomization or bootstraping versions, obtaining results similar to those obtained previously by Hoenker and Hallock (2001). Through various Monte Carlo experiments, Buchinsky (1995) demonstrates that, in the face of heterocedasticity problems, the method of estimation using randomized sub-samples for the calculation of confidence intervals is the most robust. The application of this procedure in very large samples (as is the case of the one we handle in this research) has been proven as specially adjusted. In short, with the current state of the art, contrasting hypotheses of significance is no longer a weakness in the framework of quantile regression.

5. DATA

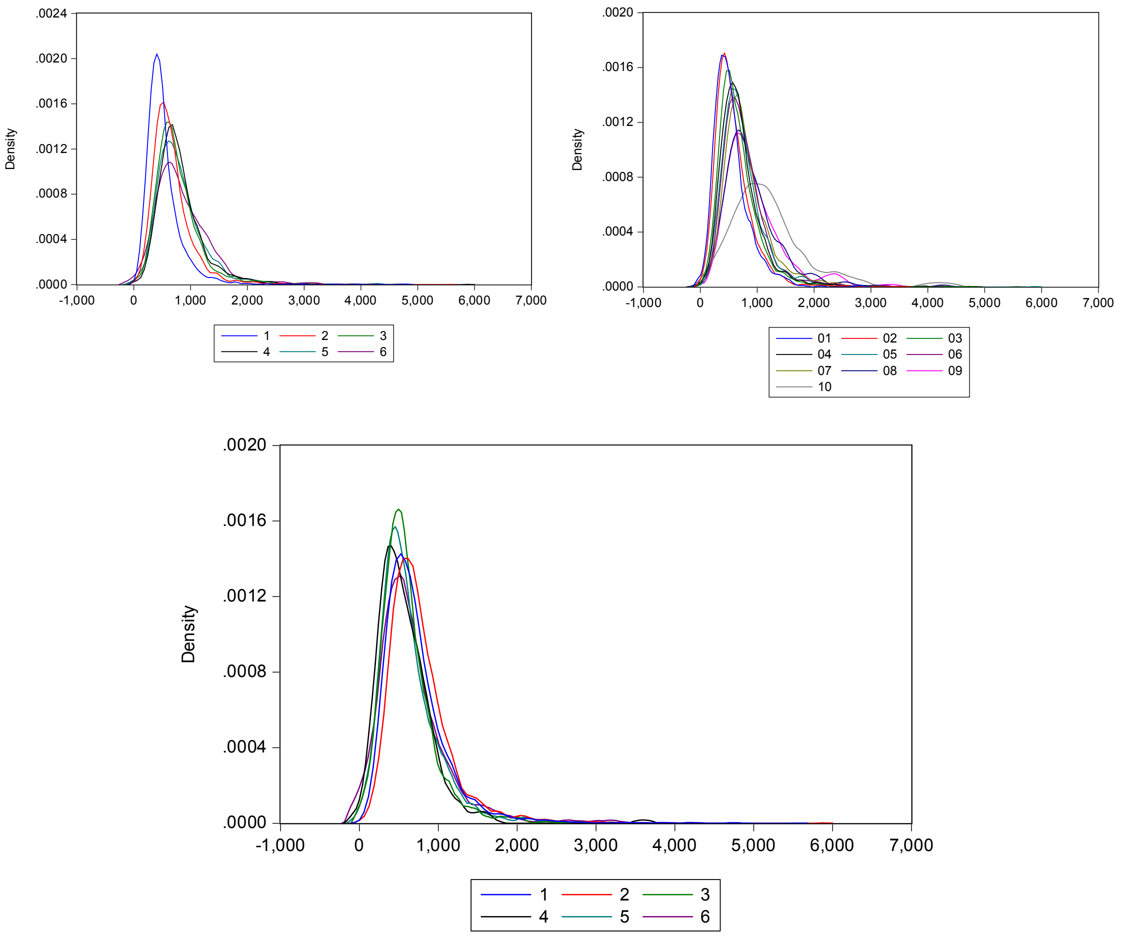
We will use the annual Household Budget Survey published by the National Institute of Statistics (INE) for 2015 (last available). This HBS is identical across EU countries so that all they can be latter integrated in a common Eurostat operation.

We decided to focus the analysis at the family level so we merged individual micro data set with families' data set. The total number of observations in each wave is composed by near 21.500 dwellings.

The endogenous variable (percentage of electricity expenditure over total revenues) clearly exhibits a non-normal distribution, and mean and median are fairly distant as the result of a large number of outliers and extreme values. The standard regression on the average appears as a poor instrument when the mean is clearly a poor representation across the sample. Additionally, some bivariate graphs illustrate that, at the bivariate level, the relationship between electricity expenditure and potential explanatory variables is not constant across quantiles for our endogenous variables.

In the survey, the more frequent family is within the interval 2-4 members (32%, 23% and 21% respectively). “Families” with just one member represent around 18% of the sample. Families of six members are present in only 6% of the sample. Literature (and logic) indicate that the larger size of households is related to greater expenditure, but the increase in such expenditure is not proportional to the increase in the number of members. This heterogeneity in the effect of membership on electricity consumption supports the thesis of the behavioural concerns cited above (see Frondel et al, 2017).

Electricity Expenditure by household size (up-left), by Family income (up-right) and by tenure regime (down)[3]



Source: Kernel density using Family Budget Survey, 2016 (INE).

6. RESULTS AND DISCUSSION

It is not surprising that family income emerges as most relevant variable when dealing with this situation. The higher the income, the lower the probability of falling into electrical poverty (the coefficients indicate a reduction of this indicator as income increases). All income cuts are significant in both OLS and quantile regressions. Just by comparing OLS coefficients with the median coefficients (q=0.5) seems easier to show the importance of outliers in defining a biased estimate if OLS parameters are used. As expected, the estimated quantile coefficients for these variables show an increase in the importance of reducing electrical poverty when considering higher values of this indicator: people in the highest part of the distribution of electrical poverty suffer a greater reduction of this situation when considering higher incomes. Non-linearity is fully confirmed by the evolution of these coefficients and the use of OLS estimators produces a

[3] The total electricity expenditure has been trunked to lower than 7000 to enhance the visualisation of the graph.

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systematic bias, and is affected by a problem of heteroscedasticity, so employing the quantile regression methodology proposed here is crucial.

The use of these estimates opens the door to more accurate policies focused directly on direct income support rather than on price reduction. Revenue policies that could be graduated to the desired level taking into account differences in parameters. The same level of reduction need not necessarily be applied for any given income, but can be done in tranches using the same coefficients shown here. Such policies could be applied through personal income tax deductions. If price reduction is the policy measure adopted (as in the recent Spanish Law), it should be assumed that the effect so far estimated would be significantly lower than the real effect because the OLS coefficients have been used. For lower incomes, the reduction by 7.8 percentage points in the electrical poverty indicator marked by the OLS coefficients underestimates the effect of the measure on the population really relevant to it, where said effect is greater than 10 points (80% quantile) or 12 points in the case of the poorest (90% quantile). Therefore, the measure is fully justified and its impact is almost double that estimated when MCOs are used.

Regression Results Indicator 1 of Electricity Poverty

*(Endogenous variable: Electricity Expenditure / Total Expenditures)*100*

Reference	Variable	OLS		0.2		0.3		0.5		0.8		0.9	
	Intercept	2.133	***	1.288	***	1.497	***	1.932	***	3.408	***	4.670	***
	Surface	0.005	***	0.003	***	0.003	***	0.004	***	0.005	***	0.007	***
	Family Size	0.753	***	0.419	***	0.472	***	0.584	***	0.750	***	0.839	***
	Resp. Age	0.004	***	0.001	*	0.002	**	0.003	***	0.006	***	0.009	***
	Gas Pov.	0.098	***	0.082	***	0.086	***	0.095	***	0.111	***	0.142	***
Andalucía	Aragón	-0.190	**	-0.133	**	-0.140	**	-0.221	***	-0.297	***	-0.418	***
	Asturias	-0.480	***	-0.346	***	-0.348	***	-0.462	***	-0.460	***	-0.520	***
	Balears	0.580	***	0.230	***	0.270	***	0.357	***	0.757	***	0.935	***
	Canarias	-0.801	***	-0.382	***	-0.481	***	-0.681	***	-1.061	***	-1.488	***
	Cantabria	-0.304	***	-0.166	***	-0.191	***	-0.345	***	-0.447	***	-0.509	***
	Castilla y León	-0.528	***	-0.387	***	-0.404	***	-0.484	***	-0.616	***	-0.695	***
	Castilla la Mancha	0.038		-0.163	***	-0.144	***	-0.141	**	0.041		0.296	**
	Cataluña	-0.308	***	-0.250	***	-0.255	***	-0.285	***	-0.333	***	-0.382	***
	Valencia	-0.202	***	-0.213	***	-0.183	***	-0.173	***	-0.202	***	-0.096	
	Extremadura	0.026		-0.078		-0.068		-0.022		0.041		-0.111	
	Galicia	-0.530	***	-0.391	***	-0.399	***	-0.436	***	-0.511	***	-0.551	***
	Madrid	-0.172	**	-0.212	***	-0.218	***	-0.257	***	-0.291	***	-0.299	**
	Murcia	0.253	***	0.049		0.066		0.183	***	0.182	**	0.300	**
	Navarra	-0.347	***	-0.231	***	-0.258	***	-0.365	***	-0.481	***	-0.561	***
	País Vasco	-0.368	***	-0.279	***	-0.308	***	-0.368	***	-0.449	***	-0.555	***
	Rioja	-0.421	***	-0.331	***	-0.332	***	-0.320	***	-0.440	***	-0.599	***
	Ceuta	-0.610	***	-0.235	*	-0.258	**	-0.361	***	-0.837	***	-0.996	***
	Melilla	0.118		0.133		0.100		-0.089		-0.566	***	-0.898	***
<500 euros	500-1000 euros	7.799	***	5.017	***	5.932	***	7.478	***	10.227	***	12.050	***

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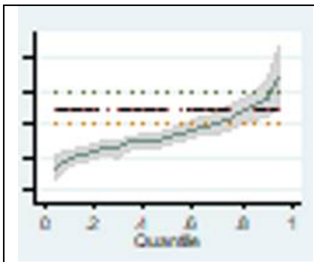
Reference	Variable	OLS		0.2		0.3		0.5		0.8		0.9	
	1001-1500 euros	3.731	***	2.112	***	2.470	***	3.221	***	4.862	***	5.808	***
	1500-2000 euros	1.865	***	1.092	***	1.256	***	1.602	***	2.316	***	2.718	***
	2000-2500 euros	0.727	***	0.424	***	0.494	***	0.607	***	0.898	***	0.993	***
	2500-3000 euros	-0.486	***	-0.330	***	-0.366	***	-0.394	***	-0.540	***	-0.608	***
	3000-5000 euros	-1.054	***	-0.738	***	-0.822	***	-0.890	***	-1.081	***	-1.269	***
	5000-7000 euros	-1.809	***	-1.228	***	-1.371	***	-1.479	***	-1.788	***	-2.109	***
	7000-9000 euros	-2.120	***	-1.442	***	-1.509	***	-1.808	***	-2.199	***	-2.400	***
	> 9000 euros	-2.244	***	-1.665	***	-1.782	***	-1.945	***	-2.391	***	-2.565	***
Condo < 10 Apt.	Isolated house	0.168	***	0.040		0.028		0.091	**	0.229	***	0.552	***
	Paired house	0.064		-0.015		0.034		0.076	**	0.181	***	0.266	***
	Condo > 10 Apt.	-0.024		0.036		0.000		-0.028		-0.089	**	-0.103	
Pop < 10k	Pop>100K	-0.102	**	-0.074	**	-0.072	**	-0.081	**	-0.117	**	-0.037	
	Pop 50k-990k	-0.084		-0.076	**	-0.048		-0.042		-0.033		-0.030	
	Pop 20k-49k	0.015		0.036		0.045		0.012		-0.010		-0.010	
	Pop 10k-20k	0.146	***	0.015		0.027		0.044		0.060		0.212	**
Normal house	Luxury house	0.074		0.031		0.061	*	0.055		0.058		0.030	
	Economic house	-0.422	***	-0.264	***	-0.227	***	-0.196	***	-0.305	***	-0.198	**
Building Age	> 25 years old	-0.123	***	-0.114	***	-0.124	***	-0.107	***	-0.040		-0.043	
Hot Water Source	Hot Water Not available	-1.664	***	-1.177	***	-1.316	***	-1.165	***	-2.157	***	-1.896	***
	Gas	-1.086	***	-0.602	***	-0.637	***	-0.857	***	-1.347	***	-1.750	***
	Liquid gas	-0.951	***	-0.447	***	-0.556	***	-0.772	***	-1.184	***	-1.490	***
	Other liquid sources	-0.713	***	-0.373	***	-0.467	***	-0.583	***	-0.973	***	-1.137	***
	Solid sources	-0.645	***	-0.226		-0.293	**	-0.584	***	-0.571	***	-0.760	**
	Solar energy	-0.607	***	-0.369	***	-0.370	***	-0.488	***	-0.696	***	-0.888	***
Heater Source	Heater Not available	-0.820	***	-0.346	***	-0.385	***	-0.497	***	-0.974	***	-1.591	***
	Gas	-0.932	***	-0.303	***	-0.424	***	-0.522	***	-1.042	***	-1.785	***
	Liquid gas	-0.676	***	-0.256	***	-0.288	***	-0.360	***	-0.862	***	-1.619	***
	Other liquid sources	-0.878	***	-0.197	***	-0.265	***	-0.466	***	-1.122	***	-2.069	***
	Solid sources	-0.981	***	-0.295	***	-0.373	***	-0.461	***	-1.273	***	-2.229	***
	Solar energy	-0.972	***	-0.631	***	-0.622	***	-0.705	***	-1.139	***	-1.392	**
Property without debts	Property with debt	0.105	***	0.085	***	0.060	**	0.056	**	0.060		0.042	
	Rented	-0.205	***	-0.159	***	-0.172	***	-0.129	***	-0.163	***	-0.239	***
	Rented (low)	-0.128		-0.138		-0.313	***	-0.079		0.228		0.129	
	Semi-free cesion	-0.108		-0.118	**	-0.203	***	-0.117	*	-0.107		-0.067	
	Free cesion	-0.066		-0.143	**	-0.008		-0.179	**	0.037		0.179	
Born in Spain	Rest EU	0.087		0.109		0.126	*	0.084		0.006		0.004	
	Rest Europe	-0.018		0.066		-0.064		0.110		0.238		0.237	
	Rest of the world	-0.144	**	-0.180	***	-0.217	***	-0.176	***	-0.068		-0.084	
< Primary Educ.	Primary Educ.	0.199	**	0.228	***	0.324	***	0.228	***	-0.128		-0.325	**
	Secondary Educ.	0.299	***	0.364	***	0.452	***	0.371	***	-0.038		-0.184	
	Highschool	0.361	***	0.354	***	0.428	***	0.362	***	0.028		-0.059	
	Prof. Formation	0.291	***	0.341	***	0.412	***	0.308	***	0.018		-0.076	
	Bachelor	0.296	***	0.334	***	0.406	***	0.296	***	-0.052		-0.181	

Reference	Variable	OLS		0.2		0.3		0.5		0.8	0.9
	Master	0.312	***	0.304	***	0.388	***	0.267	***	-0.034	-0.080
	Doctorate	0.233		0.236	**	0.351	***	0.354	***	0.079	-0.117

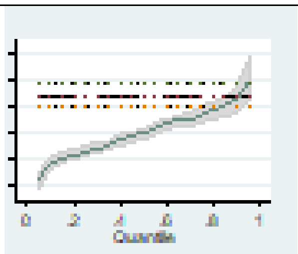
As noted above, the regional effect is extremely important in the characterization of electric poverty in Spain. All regions result in a parameter significantly different from zero when quantile regression is carried out for the poorest deciles, which does not occur using the OLS model. All the Autonomous Communities cut the level of electrical poverty with respect to the one taken as a reference: Andalusia. It is true that this cut is not very important considering the value of the coefficients, but if using the values estimated by OLS we would enter with differences of between 0.11 points to 0.8 percentage points (of lower electrical poverty), using the coefficients of the quantile regression we observe values closer to 1 point of difference in more regions.

Unfortunately, as already mentioned in previous sections, the content of the variable region is, by nature, imprecise, because it probably contains several mixed factors. In any case, the inclusion of the rest of the available control variables (such as income, population density, surface area and ownership of the dwelling, etc.) will probably isolate in this variable almost exclusively the climate factor that we understood to be fundamental in our previous explanations (in both extreme cold and heat conditions). Note that the reference region, Andalusia, is the one that suffers the worst extreme heat conditions in a large number of months per year. Considering these differences, we may have a new mechanism to refine the implementation of the policy of reducing energy poverty also taking into account the geographical nature.

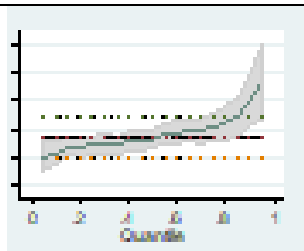
Electricity poverty. Some Quantile Coefficients



Surface



Family Size



Age of respondent

These graphs are useful to highlight once again the important bias that occurs when observing the parameters usually used (the OLS) when the interest is evidently focused on a very specific section of the sample (in our case, the higher quantiles, as the poorest households in terms of electricity). The rest of the graphs can be seen in the annex.

As expected, the type of fuel used to heat the home and/or water in the home is relevant. One point of reduction in poverty is showed when fuels other than electricity are used. It should be borne in mind that, as a basic control variable, the variable "gas-related energy poverty" has been included separately, in such a way that these coefficients we are now talking about would reflect how using fuels other than electricity sharply reduces poverty (almost two points in the

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poorest households observing the quantile coefficients). This observation leads to the need to leverage investment in more efficient and cheaper heating systems such as gas versus electricity to reduce the electricity poverty gap.

Looking briefly at the rest of the coefficients obtained (without going into the detail of all of them), it does seem interesting to show how, and for example, the housing ownership regime is not significant in the OLS estimation. Conversely, it is in the quantile regressions, where families with rented housing do see their poverty gap slightly reduced with respect to the rest of situations. Perhaps this is related to the excessive stock of typically owned dwellings in Spain, where most families have large mortgages with little capacity to change their instalments during periods of crisis, a differential in families with rented housing who can probably partially readapt their housing expenditure during these periods.

Going to the characteristics of the parameters estimated for the different educational levels, it should be noted that, here, it is interesting to pointing out that these levels are significant for the richest or middle class deciles (from 20% to 50%), but not for the poorest deciles (80% and 90%). This fact would not have been observed considering only the results of OLS (where none of the levels is significant). It is also interesting to comment that the parameters (around the 0.35 points of greatest poverty before any educational level compared to the reference, those without formal education) are always positive and not different among the educational levels.

In short, all of these variables emerge as "red flags" when policy measures are taken to reduce electrical poverty. The effect of policies such as subsidies to change the heating system or income tax reductions for households with property debts should only be targeted at lower-income households if the aim is to reduce electricity poverty. Measures aimed at reducing consumption (as part of reducing the climate change impact of the use of this source of electricity) should clearly focus on changing the heat source.

7. CONCLUSIONS

In this article, the crucial issue of the electricity poverty in developed countries has been characterised using the Spanish situation in 2016 as a case study. Although the study of energy poverty has been a common topic in the economic literature, it has been usually focused in the less developed countries case. Because of inequalities emergence and climate issues interest in developed countries, studying this situation is nowadays gaining momentum.

Traditionally, electricity demand and, to some extent, poverty research has been conducted using regression models based on the method of estimating least squares coefficients. Both because the focus of poverty is concentrated on very specific distribution cuantiles and because the impact of some explanatory variables can change drastically if the distribution of the variable is considered, the findings of this article are especially important when considering alternative policy measures to avoid electrical poverty.

In this article, we have shown the crucial differences in the drivers dealing electricity poverty if they are estimated using OLS against Quantile regressors. Clearly, the use of the firsts produces a distorted draw of the reality, making a bad interpretation of the potential effect of public or private stimulus to reduce poverty.

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As it could not be otherwise, in our research, income is shown as the most important variable in relation to electrical poverty, but also other variables such as the characteristics of housing tenure, or regional differences are crucial when interpreting the effect of different anti-poverty policies.

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ANNEX

Descriptive statistics of the explanatory variables

		2016		2012	
Group	**Variable**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
	Aragón	0.044674	0.206593	0.044344	0.205863
	Asturias	0.040442	0.196997	0.038621	0.192694
	Balears	0.034645	0.182882	0.036992	0.188747
	Canarias	0.04472	0.206694	0.045135	0.207605
	Cantabria	0.034553	0.182648	0.03555	0.185169
	Castilla y León	0.067219	0.250406	0.066307	0.248823
	Castilla la Mancha	0.055533	0.229022	0.055512	0.228981
	Cataluña	0.091511	0.288342	0.089247	0.285106
	Valencia	0.077755	0.267791	0.079289	0.270196
	Extremadura	0.045503	0.208409	0.045461	0.208318
	Galicia	0.06087	0.239096	0.060816	0.238998
	Madrid	0.07458	0.262719	0.072216	0.258852
	Murcia	0.040856	0.197961	0.041413	0.199247
	Navarra	0.033724	0.180523	0.035224	0.18435
	País Vasco	0.101035	0.301382	0.097855	0.297125
	Rioja	0.033126	0.17897	0.033595	0.18019
	Ceuta	0.005245	0.072234	0.005351	0.072957
	Melilla	0.005567	0.074406	0.005863	0.076347
	Pop 50k-990k	0.123948	0.329529	0.117584	0.322123
	Pop 20k-49k	0.152749	0.359754	0.150342	0.357415
	Pop 10k-20k	0.104072	0.305361	0.10865	0.311207
	Pop < 10k	0.243892	0.429438	0.244242	0.429647
	Intermediate density	0.236531	0.424962	0.23461	0.423765
	Low density	0.288567	0.453106	0.293146	0.455215
	Paired chalet	0.24472	0.429931	0.251733	0.434019
	Condo < 10 apartments	0.177088	0.381752	0.180587	0.384685
	Condo > 10 apartments	0.470899	0.499164	0.460472	0.498447
Region	Other	0.001288	0.03587	0.001163	0.034088

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		2016		2012	
Group	**Variable**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Dwelling age	More tan 25 years	0.652404	0.476218	0.63045	0.482694
	Surface	101.1462	49.61235	101.6724	49.6414
	Electricity	0.229998	0.420841	0.217114	0.412291
	Gas	0.394801	0.488819	0.374064	0.483891
	Liquid gas	0.238417	0.426125	0.27351	0.445771
	Other liquid sources	0.117598	0.322139	0.120748	0.325842
	Solid sources	0.005659	0.075015	0.005444	0.073585
	Solar energy	0.010674	0.102765	0.007073	0.083804
Water	Not available	0.000046	0.006783	0.0000465	0.006821
	Electricity	0.140189	0.347191	0.138849	0.345797
	Gas	0.332505	0.471122	0.309851	0.462443
	Liquid gas	0.025673	0.158161	0.028384	0.166071
	Other liquid sources	0.142397	0.349465	0.149598	0.356685
	Solid sources	0.02259	0.148597	0.017403	0.130769
	Solar energy	0.00161	0.040097	0.000791	0.028115
Heater	Not available	0	0	0.0000931	0.009647
Income	500-1000 euros	0.171659	0.377092	0.172305	0.377654
	1001-1500 euros	0.207177	0.405293	0.203806	0.402836
	1500-2000 euros	0.167472	0.373405	0.171839	0.37725
	2000-2500 euros	0.139821	0.346809	0.137267	0.344137
	2500-3000 euros	0.10789	0.310249	0.114234	0.318102
	3000-5000 euros	0.131125	0.337545	0.131171	0.337595
	5000-7000 euros	0.021624	0.145456	0.021125	0.143805
	7000-9000 euros	0.006257	0.078856	0.003583	0.059751
	> 9000 euros	0.00253	0.050241	0.001582	0.039745
	Property with debt	0.302001	0.459136	0.320087	0.466521
	Rented	0.117184	0.321647	0.10772	0.310033
	Rented (low payment)	0.01095	0.104071	0.012936	0.113
	Semi-free cession	0.027421	0.163311	0.027919	0.164744
House tenure	Free cession	0.019462	0.138144	0.018426	0.13449
	Rest EU	0.021256	0.14424	0.023638	0.151921
	Rest Europe	0.003221	0.05666	0.002978	0.054491
Nationality	Rest of the world	0.054566	0.227137	0.053325	0.224685
Employment	Unemployed	0.434967	0.495764	0.439719	0.496364
Size	Household size (OECD)	1.770412	0.547907	1.806831	0.557249
Age	Age main income contributor	55.6213	14.93647	54.29091	15.30132

Source: Family Budget Survey 2012 and 2016 (INE) and own calculations

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