The Potential for Segmentation of the Retail Market for Electricity in Ireland

Abstract: We estimate the gross margin that is earned from the supply of electricity to households in Ireland. Using half hourly electricity demand data, the system marginal price (also called the wholesale price) and the retail price of electricity, we analyse how the gross margin varies across customers with different characteristics. The wholesale price varies throughout the day, thus, the time at which electricity is used affects the gross margin. The main factor in determining gross margin, however, is the level of demand.

The highest gross margins are earned from supplying customers that have the following characteristics: being aged between 46 and 55, having a household income of at least €75,000 per annum, being self–employed, having a third-level education, having a professional or managerial occupation, living in a household with 7 or more people, living in a detached house, having at least 5 bedrooms or being a mortgage holder.

An OLS regression shows that gross margin is partly explained by the energy conservation measures which are present in a household; the number of household members; the number of bedrooms; age; occupation; and accommodation-type.

Key words: Electricity demand, market segmentation, gross margin, Ireland.

1. Introduction

Smart meters hold a lot of promise. Smart meters will enable demand side management for small electricity users through real time pricing and smart appliances. Smart meters will help with the integration into the electric power system of micro-generation and micro-storage, and of hybrid and all-electric vehicles. Smart meters will also yield unprecedented amounts of information about consumer behaviour. At present, the typical power company knows its clients' monthly electricity use. In the future, power companies could know electricity use per minute – if so desired.

In other markets, similar revolutions in data availability have led to market segmentation. This can be benign, as in the case of targeted promotions (e.g., supermarkets) or pricing (e.g., airlines) but in other cases regulators had to step in to prevent exclusion (e.g., health insurance). Because the wholesale price of electricity varies sharply over the diurnal cycle, high-frequency use data may turn out to be very valuable to power companies. Of course it is important that electricity providers identify the customers that generate the largest gross margins. In this way, suppliers can more efficiently target, satisfy and retain their most profitable customers. This is easily done through marketing targeted at particular groups or particular locations. At the same time, competition is far from perfect in the electricity market and regulation is tight. Older and lower educated people are less likely to switch electricity provider (European Commission, 2009), so that less profitable clients may stay with the incumbent while more profitable ones join the new entrant[1]. The new entrant would have a strong incentive to encourage that, say through selective advertising. However, electricity is seen as an essential good and there would be political pressure that the "vulnerable" (e.g., elderly, lower educated) would not pay "excessive" prices. In the current system, there is an implicit subsidy from the more profitable customers to the less profitable ones. In the future, this may become an explicit subsidy, or the regulator may take other action. Rural electricity customers are more expensive to connect, and while these customers do pay a higher fixed fee per month, utilities are not allowed to refuse to provide service to them. Similar restrictions may (have to) be imposed on otherwise unprofitable clients. Thus it is important to analyse whether the availability of time-of-use data, as provided by smart meters, may facilitate adverse selection in the retail market for electricity (Joskow and Tirole, 2006).

In this paper, we use data from the smart meter trial in Ireland to test whether profitability varies systematically between different types of households. Specifically, we estimate the gross margin earned from the supply of electricity. Using half hourly electricity demand data, the half-hourly system marginal price (SMP), some of the additional costs of supplying electricity, and the retail price of electricity, we analyse how the gross margin varies across customers, using their characteristics as revealed in a detailed user survey. We also run an OLS regression to establish which household characteristics are statistically significant in explaining gross margin. To the best of our knowledge, we are the first to do this for any country.

In Ireland electricity is bought and sold through the All-Island electricity market which commenced operations in November 2007. The Single Electricity Market (SEM) operates on the basis of a mandatory pool market. All electricity generated on or imported onto the island of Ireland must be sold to this pool. In addition, all wholesale electricity for consumption on or export from the island of Ireland must be purchased from the pool market. Suppliers purchasing energy from the pool pay the generators the SMP, capacity costs[2], and system charges. The SMP is a single island-wide price for each half hour trading period. It is determined via market scheduling and pricing software for each half hour trading period.

There is a large literature in the marketing sphere that examines how businesses should identify and subsequently target their most profitable customers (see for example Kumar, Petersen and Leone, 2010, Lee and Park, 2005) This is important in the Irish electricity market where increased competition in recent years has encouraged many customers to switch providers. In such a market, businesses should realise that retaining customers is significantly less expensive than attracting new

[1] Indeed Giulietti et al. (2005) found that households in the UK that had pre-payment meters installed and OAP-households were significantly less likely to be aware of the possibility of switching gas supplier

[2] Capacity costs are payments to generators for making capacity available to the market, and vary by half-hour.

ones (Jeffrey and Franco, 1996, Reichheld and Sasser 1990). By identifying the gross margin across different groups of customers, electricity suppliers can more efficiently target, satisfy and retain their most profitable customers, thus increasing profits. The methods employed in this paper can be easily adopted for studies of gross margin in other countries where high-frequency household electricity demand data are available.

The paper proceeds as follows: The data and methods used are described in the next section. The results are presented in Section 3. Section 4 concludes.

2. Data and Methods

We calculate the gross margin for electricity supplied to 4,232 households in every half hour period from the 14th of July to the 31st of December 2009. While we do not account for all the costs that electricity supply companies incur in bringing electricity to consumers, in our calculation we do account for some of the more significant costs; with a particular emphasis on those that vary by time of day. Furthermore, we assume the price that the electricity supply companies pay is the wholesale price, as determined by the SMP (system marginal price), and thus do not take account of instruments, such as contracts for differences, used to hedge against price fluctuations. The costs which we include in the calculation of gross margin are as follows:

The SMP (system marginal price), which is the wholesale price of electricity. The Single Electricity Market Operator (SEMO) provides data on SMPs for every half hour trading period of 2009 (SEMO, 2010)[3]. The average SMP in 2009 was 3.5 cent/kWh.

Capacity charges: the capacity payments mechanism is a source of revenue for generators that supply generation capacity to the market. Capacity payments to generators are recouped from supply companies that pay capacity charges, which vary by half hour[4]. The average capacity charge in our data was €0.008/kWh.

Transmission and Distribution Use of Service Charges (TUoS and DUoS): TUoS charges consist of a network transfer charge (€0.002/kWh), a system services charge (€0.002/kWh), and a demand-side management charge (€0.0002/kWh); which apply in all half-hour periods. There is an additional component to the TUoS charge that applies only during day-time hours; that is the network capacity charge (€0.004/kWh). The DUoS charge is fixed during all hours of the day and was set at €0.030/kWh for the period up to end-September 2009, when it increased to €0.036c/kWh[5].

Imperfection charges: these do not vary by half hour and were set at €0.0033/kWh up to end-September 2009, when they decreased to €0.0028/kWh

Loss adjustment factor (LAF): we take account of the fact that not all electricity bought by the electricity supply company is brought to the consumer due to losses along the network. Losses vary

[3] Due to the absence of demand data from the Smart Metering trial prior to 14th July 2009, only SMP data after this date were needed for our analysis

[4] For further details of the capacity payments mechanism see CER (2011b). Data on capacity payments are available from SEM-O, www.sem-o.com

[5] Further information on TUoS charges are available from Eirgrid (2008), and further information on DUoS charges are available from ESB Networks (2009)

by time of day and are higher when the network is more congested. We follow the CER methodology (CER, 2011a) and apply the following loss adjustment factors: Peak = 1.12, Day = 1.11, Night = 1.09

Thus, the gross margin of electricity supply to a particular customer at a particular day equals:

$$G_i = \sum_{h=1}^{48} (P - LAF_h * (W_h + DUoS + TUoS_h + CapCharge_h + ImperCharge)) * D_{i,h}$$

where P is the retail price (in cent per kilowatt hour (kWh)), which is constant over time in Ireland; LAF_h is the loss adjustment factor, which has a time-of-day component; W_h is the wholesale price or SMP (in cent per kWh), which varies per half hour h; *DUoS,* as discussed above, does not vary by time of day, while $TUoS_h$ has a time of day component; $CapCharge_h$ is the capacity charge, which varies by half-hour; *ImperCharge* is the imperfection charge which does not vary by time of day; $D_{i,h}$ is the demand for electricity (in kWh) of customer i at time h; and finally G_i is the gross margin (in € cents per day) of customer *i.* We find the total gross margin earned for each of these 4,232 customers in the second half of 2009 and we then compare the gross margin of households with different characteristics. By dividing gross margin by total demand over the period we can analyse the average margin earned for different types of households.

The retail price of electricity was 16.4 cent/kWh between January and April 2009. In May 2009 it decreased to 14.6 cent/kWh before falling to 14.1 cent/kWh in October 2009 (ESB Customer Supply, 2010). All households face the same retail prices, as determined by the Commission for Energy Regulation. We use the standard 24 hour unit cost so that the retail price does not vary by time of day.

We use data on half-hourly household electricity demand in the second half of 2009 that was collected for the purpose of Smart Metering Customer Behaviour Trials (CBT) carried out by the Commission for Energy Regulation (CER). According to the CER (CER, 2011a), this smart metering CBT was one of the most statistically robust trials of its type carried out internationally, and thus provides a rich data source for analysing patterns of electricity usage. As outlined by CER (2011a), the optimal sample size for the trial was determined to be approximately 4,300 consumers, thus, in order to allow for attrition over 5,000 consumer of Electric Ireland[6] were recruited. The consumers were invited to participate in the trial on a phased basis and were profiled in order to ensure they were nationally representative. To further ensure that those participating in the trial were representative, the CER also conducted non-response surveys of those electricity consumers who chose not to participate in the trial.

The data provides demand data for the second half of 2009 (the benchmark period for the smart metering trials) and all of 2010 (the test period). The benchmark period ran from the 1st of July to the 31st of December 2009[7]. We chose to analyse electricity use in 2009 because during the test period participants were put on various time-of-use tariffs and other demand-side management

[6] At the time of the CBT Electric Ireland was the only retail electricity supply company in Ireland (CER, 2011a).

[7] However, data from the first two weeks of July were subsequently omitted from the final dataset due to incomplete data collection in this period (CER, 2011)

stimuli were also used. Average electricity demand in our sample was 2115kWh. More detailed descriptive statistics can be found in Table 1.

[Table 1 about here]

The main factor driving gross margin is customer demand. Any changes in demand will result in changes in gross margin of the same proportion, ceteris paribus. Average electricity demand by time of day can be seen in Figure 1. The cost of supplying electricity varies with changes in aggregate demand in the residential sector. SMPs are highest between 18.30 and 19.00 on both midweek and weekend days. An increase in the SMP has a negative effect on gross margin but because such an increase is associated with a period of higher demand in most households, the net effect on gross margin is positive. The average SMP by time of day in 2009 is displayed in Figure 2.

[Figure 1 about here] [Figure 2 about here]

Using the Smart Metering dataset we can analyse how the total gross margins and average margins vary across customers with different characteristics. The dataset provides information on household income and a range of socio-economic and household characteristics of respondents. The characteristics we include in this analysis are the respondents' employment status, social status, age and gender. We also consider the education level of the household's chief economic supporter (CES), the number of people in the household, the household's income level, the type of accommodation, the number of bedrooms and type of tenure. The number of respondents in each category can be seen in Table 2. One drawback of this data is the low response rate to the income question; out of the 4,232 people in the sample only 1,942 provided income data. This results in a significant drop in the sample size in the model specification which includes income.

Having examined how gross margin varies across households with different characteristics, we run an OLS regression to establish which factors are most important in determining the gross margin.[8] The model is specified as follows:

$$y_i = x'_i\beta + \epsilon_i$$

where y_i is the gross margin earned from the supply of electricity to household *i*. x_i is a vector of characteristics of household *i* and β is a vector of parameters. ϵ_i specifies the error term. The explanatory variables comprise a range of respondent and household characteristics which we think might affect the gross margin. The respondent characteristics include age, gender, social class and employment status. We also include the education level of the CES. Many of these socio- economic characteristics were found to be statistically significant in studies of household energy demand (Leahy and Lyons, 2010, Druckman and Jackson, 2008 and O'Doherty et al., 2008).

The household characteristics include the type of accommodation because different accommodation types have very different patterns of electricity demand (Leahy and Lyons, 2010, O'Doherty et al.,

[8] Note that households are price-takers. The gross margin thus follows from household decisions on how much power to use and when.

2008). We control for the number of bedrooms and the number of household members because these are positively associated with electricity demand (Leahy and Lyons, 2010). We also control for the number of household members that are at home during the day. As the SMP varies throughout the day, we expect that households that use electricity at the most expensive times will have lower gross margins. Another explanatory variable is the number of electrical appliances present in the accommodation. We also include the type of cooker present in the household. The year the accommodation was built proved significant in explaining household energy use and electricity demand in Ireland (Leahy and Lyons, 2010), thus we feel it may also play a role in explaining gross margin. The annual income earned by the household is also included as a control variable. Electricity demand increases with income so we expect income to be statistically significant in this model.

The dataset provides information on a number of energy saving features present in the household which we include as dummy variables in our model. We expect that the gross margin earned from the supply of electricity to households that are concerned with energy conservation will be lower than that of other households. The variables we include are attic insulation, external wall insulation, lagging jacket and concern for the environment[9].

3. Results

3.1. Descriptive statistics

Table 2 shows the total gross margin earned across households with different characteristics in 2009. Table 2 also shows the average margin i.e., gross margin divided by total electricity demand over the period.

[Table 2 about here]

The descriptive statistics show that during the period analysed, when households are divided by age of respondent, the average gross margin is highest for respondents in the 46-55 year old age group. In general, the relationship between gross margin and age is inverse-U-shaped.

The data also show that gross margin is highest for the richest households in our sample, as gross margin is so closely linked to demand this is not surprising. We cannot say, however, that gross margin always increases with income.

Considering employment status, the self employed, especially those with employees, generate the highest gross margin. This could be because these customers work from home and thus demand more electricity than their counterparts who work outside the home. The self-employed may also be using electricity at times when the cost of supplying electricity is relatively low, thus boosting the gross margin. Retired customers generate the smallest margin, this concurs with research by Leahy and Lyons (2010) who found that households in which the CES is retired use less electricity compared to households whose CES is in any other employment category.

[9] An additional variable that may explain patterns of electricity demand, and thus margin, would be the weather; however, we cannot control for this due to a lack of half-hourly weather data. Furthermore, it is a variable which does not vary much in Ireland at the household level.

With regard to education levels, households whose CES is educated to third level generate higher gross margins than households whose CES has lower educational qualifications. Leahy and Lyons (2010) found that the relationship between electricity demand and education is U-shaped, however, the Smart Metering data does not specify different levels of post secondary education so we cannot tell if this inverse-U-shaped relationship exists for gross margin.

The data show that customers in different social-class categories also generate different gross margins. Margin is highest from those with a social status of higher-managerial, administrative or professional; these are also the highest earners of all social-status categories, so, this result is not surprising.

As expected, the gross margin increases as the number of people living in a household increases. Furthermore, as the number of bedrooms increases so too does the gross margin earned by the electricity supplier. This is probably because homes with a large number of bedrooms may have a larger total floor space, and thus require more electricity for heating and lighting.

We also find that gross margins differ greatly across different types of accommodation. Customers living in apartments generate lower gross margins per half hour, and over the period of the analysis, compared to customers with any other characteristic considered in this study. Leahy and Lyons (2010) found that apartment dwellers demand lower amounts of electricity than those living in houses. This is probably because apartments are smaller and thus, easier to heat and they contain fewer electrical appliances due to space restrictions[10]. The biggest gross margins, in terms of accommodation types, can be earned on detached houses.

While gross margins do vary across households with different characteristics, results show that the average margin is stable, at approximately 3 cent/kWh. This indicates that the time at which electricity is used does not lead to differences in the average margin earned from supplying different households. It is clear that almost all of the variation in gross margin is explained by changes in the level of demand. Figures 3A, 3B and 3C show how the pattern of electricity demand varies with the age category of the respondent, the income level of the household and the employment status of the respondent. Although the level of demand is seen to vary across households, to our surprise, the pattern of demand is very similar. For this reason, the average margin is almost the same for all households.

[Figures 3(A-C) about here]

3.2. Regression results

The results in Table 2 are univariate tabulations. This may be misleading: Income, age, and education are correlated. We therefore show the results of an OLS regression explaining gross margin in Table 3. We do not include household electricity demand as an explanatory variable because demand is used to compute the dependent variable. The variables that we do include in the model help explain approximately 38% of the variation in gross margin. Due to the large number of explanatory variables in the model, only the statistically significant results are discussed. The results discussed

[10] Those living in apartments own 7 appliances whereas the average for the rest of the sample is 10.

below are based on a regression which includes income as an explanatory variable; however as only 1,942 households in the sample provided income data this results in a significant drop in the number of observations. As a sensitivity check, we also ran the model omitting the income variable, this caused the sample size to increase to 4,226 observations; in general the pattern of the results holds.

[Table 3 about here]

Results show that being aged between 26 and 35 is negatively associated with the gross margin. This is probably to do with different demand patterns exhibited by people of different age groups. Relatively younger respondents may not be at home as often or they may allocate time towards activities that do not require as much electricity as those activities pursued by their older counterparts. Interestingly, the coefficient for respondents aged over 65 is positive and significant. This contradicts the result displayed in Table 2 where we saw that the oldest respondents generate relatively low gross margins.[11] This may be because elderly people use little electricity in absolute terms but a lot relative to their income and household size. However, when we run the model on the full sample, omitting the income variable, the statistical significance of this result does not hold.

Consistent with the result in Table 2 is the fact that the self-employed generate larger gross margins than their counterparts who are employees. As stated earlier, this may be due to increased electricity demand that may occur if one works from home, especially at times during the day when the SMP is relatively low. Only two of the social status variables are significant in the model: Being in the "Managerial, Administrative, Professional" category is positively associated with gross margin, which is consistent with the result in Table 2; this effect disappears when the model is run on the full sample, omitting income. Being a farmer is negatively associated with gross margin. This may be because farmers tend to spend more time outdoors and demand less electricity than those in other social classes. Or, it may be that rural households use power showers and electric cookers at peak hours. Interestingly, of the categories of annual household income in the dataset, none are significant predictors of gross margin in the model.[12] As expected, living in an apartment is negatively associated with gross margin. This is probably because apartments contain fewer rooms than other types of accommodation and, as a result, electricity demand is lower; while the sign of the coefficient remains negative in our specification omitting income, the significance of this result does not. Conversely, living in a detached home is positively associated with gross margin. While Table 2 showed that the gross margin varied by type of tenure, the results from the regression analysis show that, after controlling for confounding factors, type of tenure does not have a significant effect on gross margin[13]. Living in accommodation with only one bedroom is significantly and positively associated with gross margin. This result is surprising for two reasons. First, it contradicts the results displayed in Table 2 which indicate that living in accommodation with one

[11] This result refers only to those respondents who provided income data and not to the full sample. 324 respondents who are over 65 provided income data. They must also be high users of electricity as they generate relatively high gross margins of €56 on average. There are 953 respondents aged over 65 in the full sample and their gross margin is slightly lower at €52 on average.

[12] The Smart Metering dataset specifies these income categories so it is not possible to include income as a continuous variable.

[13] However, results from the regression based on the full sample indicate that both being a mortgage holder and renting from a local authority are positively associated with gross margin

bedroom is negatively correlated with gross margin. Second, this result is surprising because one bed-roomed accommodation is likely to have a smaller floor space than accommodation comprising of more bedrooms. Thus, one would expect it to have a lower electricity requirement. It must be that respondents living in one bed-roomed accommodation use electricity for heating and cooking as opposed to other fuels such as natural gas which may be used in larger homes. Upon closer examination we see that only 17 respondents who live in one bed-roomed accommodation provided income data and their gross margin is €47 on average. There are 46 respondents in total who live in one bed-roomed accommodation. The gross margin for all of the respondents in this category is lower at €41 on average, thus it is unsurprising that this result disappears when the model is run on the full sample. The coefficients for accommodation with 4 bedrooms and at least 5 bedrooms are positive and significant. The higher space heating and lighting requirements associated with having more bedrooms may explain this result.

Unsurprisingly, gross margin increases as the number of people living in the household increases. The number of electrical appliances present also proved statistically significant in explaining gross margin. The coefficient is positive indicating that as the number of appliances increases, so too does the gross margin.

Some of the energy conservation variables proved significant in the model. Having a lagging jacket, attic insulation or external wall insulation are all negatively associated with gross margin[14]. This may be because those households that have invested in these measures probably have lower electricity demand than households that are not concerned with energy conservation. This is an important result as it indicates that energy-saving measures are clearly not in electricity supply companies' interests. This issue is discussed in Vine et al. (2003); the authors note that in competitive electricity markets it is in the interests of neither the wholesale nor the retail electricity supplier to encourage end-user energy conservation. In the case of the electricity suppliers, in order to maximise profits their objective will be to "maximize kWh sales" (Vine et al., 2003).

The type of cooker was insignificant in explaining gross margin, which is unsurprising as the majority of people in the dataset own an electric cooker[15]. The education level of the CES and the year the accommodation was built were not important in explaining gross margin.

3.3. Smart meters and market segmentation

Could the availability of detailed time-of-use data allow electricity supply companies to identify and thus target their most profitable customers? Such an issue would be of concern to policymakers who may want to prevent adverse selection occurring in the retail market for electricity. Interestingly, our results show that the availability of detailed time-of-use data does not constitute a "revolution" in market segmentation for electricity supply companies. We find that the most important factor driving gross margin is the *level* of electricity demand, rather than the time of day at which it is used;

[14] When the model is run on the full sample the effect of lagging jackets and wall insulation is no longer significant, however the result that attic insulation results in a decline in gross margin remains strongly significant

[15] Of the 1,946 people who provided income data, 1404 had an electric cooker

utilities already have data on the total amount of electricity demanded. The correlation between total gross margin per household and total electricity demand for the households in our sample is 0.967; this is illustrated in Figure 4.

[Figure 4 about here]

Joskow and Tirole (2006) outline how competitive screening and adverse selection by electricity suppliers can arise in a situation where electricity consumers have real-time meters installed and non-uniform pricing is prohibited. The authors note similarities with issues arising in the insurance markets as discussed by Rothschild and Stiglitz (1976). However, we have shown that, in Ireland, this issue is unlikely to arise; the profitability of customers is driven by the level of electricity demand, as opposed to the time of day at which the electricity is used. This result is largely driven by the fact that the diurnal pattern of electricity demand for households in Ireland differs very little by household type, as illustrated by Figures 3(A-C).

4. Discussion and conclusion

In this paper we estimate the gross margin that is earned from the supply of electricity to 4,232 households in Ireland. Gross margin varies throughout the day with changes in customer demand and changes in the SMP. In a period of high demand gross margin increases even though the supply of electricity is more expensive at these times as indicated by higher SMPs.

We compare the degree to which gross margin varies across customers with different characteristics. We find that the highest gross margins are earned from supplying customers that have the following characteristics: being aged between 46 and 55, having a household income of at least €75,000 per annum, being self-employed, having a third level education, having a professional or managerial occupation, living in a household with 7 or more people, living in a detached house, having at least 5 bedrooms or being a mortgage holder.

The average margin is 3 cent/kWh for each group of households considered in this analysis. Upon further investigation we find that the pattern of electricity used does not differ greatly between households with different characteristics. Almost all of the variation in gross margin is explained by the level of demand rather than the time at which electricity is used.

We run an OLS regression in order to establish which characteristics are important in explaining gross margin at the household level. Results show that gross margin is partly explained by the energy conservation measures which are present in a household, the number of household members, the number of bedrooms, and the age, social status and occupation of household members.

Interestingly we find that smart metering data will not provide electricity supply companies in Ireland with any additional information on which groups of customers are the most profitable. We find that gross margin is driven by the level of electricity demand, rather than the time at which it is used. In Ireland the pattern of electricity demand is highly similar across all households; this may evolve in the future as household adopt load-shifting devices, for example electric vehicles, at different rates. However, as current patterns of electricity demand stand, data on gross demand is as valuable to electricity supply companies as time-of-use data would be.

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Table 1. Descriptive Statistics

	Mean	Std. Dev	Min	Max
SMP per half hour (€/kWh)	0.040	0.027	0.004	0.581
Capacity charge per half hour (€/kWh)	0.008	0.009	0.000	0.139
Electricity demand per half hour	0.508	0.701	0.000	8.020
Total electricity demand	2114.769	1048.827	93.714	10623.630
Gross margin per half hour	0.008	0.004	0.000	0.051
Gross margin per household	62.760	32.515	-0.511	344.248

Table 2. Total Gross Margin in 2009

	Mean (€)	Std. Dev (€)	Min (€)	Max (€)	Gross Margin /Demand (€/kWh)	n
Age of respondent						
Aged 18-25	59	31	12	132	0.0303	16
Aged 26-35	60	30	6	224	0.0296	420
Aged 36-45	68	32	3	282	0.0294	905
Aged 46-55	70	34	4	344	0.0302	1031
Aged 56-65	61	32	5	294	0.0301	883
Aged over 65	54	30	-1	306	0.0297	953
Not specified	69	42	14	173	0.0316	24
Household income						
< €15,000	48	28	6	184	0.0304	185
€15,000 - €30,000	59	32	6	294	0.0300	292
€30,000 - €50,000	68	34	5	282	0.0295	463
€50,000 - €75,000	64	30	2	181	0.0299	634
> €75,000	74	34	6	224	0.0300	372
Employment Status						
Employee	65	31	-1	239	0.0297	2001
Self-employed with employees	84	47	13	344	0.0304	232
Self-employed without employees	72	37	4	294	0.0304	303
Unemployed seeking work	59	30	8	200	0.0301	200
Unemployed not seeking work	59	30	8	154	0.0304	170
Retired	54	28	2	306	0.0298	1285
Carer	68	31	16	159	0.0297	41
Education level of CES						
No formal education	55	26	12	122	0.0291	59
Primary education	53	31	6	306	0.0298	475
Junior Certificate	63	30	-1	200	0.0297	712
Leaving Certificate	62	31	4	294	0.0296	1174
Third level	67	34	3	344	0.0301	1580
Not specified	64	35	4	245	0.0300	232
Social Status						
AB: Managerial, administrative, professional	72	38	7	344	0.0301	642
C1: Supervisory or clerical, junior managerial, administrative or professional	66	33	3	294	0.0299	1134
C2: Skilled manual workers	64	29	4	152	0.0295	706
DE: Semi and unskilled manual workers, casual workers, those in receipt of state benefits	56	29	5	306	0.0298	1593
F: Farmers	62	41	-1	197	0.0303	113
Not specified	63	32	9	158	0.0297	44
Gender of respondent						
Male	64	33	2	306	0.0300	2127
Female	61	31	-1	344	0.0297	2105
Household Size						

1 person household	53	29	14	181	0.0306	51
2 person household	57	28	2	294	0.0299	1340
3 person household	67	26	5	184	0.0297	740
4 person household	76	32	-1	344	0.0293	751
5 person household	88	34	7	245	0.0291	361
6 person household	93	32	5	211	0.0291	140
7 person household	96	31	51	224	0.0293	29
8 person household	96	32	45	139	0.0288	7
9 person household	94	20	80	109	0.0284	2
10 person household	129	.	129	129	0.0294	1
12 person household	98	91	34	162	0.0341	2
Not specified	38	23	4	282	0.0308	808
Accommodation Type						
Apartment	34	18	5	95	0.0306	72
Semi-detached	59	29	3	265	0.0298	1351
Detached	72	36	4	344	0.0299	1121
Terraced	54	29	6	274	0.0299	613
Bungalow	66	32	-1	306	0.0298	1068
Not specified	58	29	8	94	0.0291	7
Tenure						
Renting Privately	49	28	9	129	0.0310	71
Renting from local authority	55	27	8	136	0.0304	228
Owned outright	60	32	-1	306	0.0299	2215
Mortgage holder	68	34	3	344	0.0296	1706
Other tenure	59	28	21	122	0.0308	12
Number of bedrooms						
1 bedroom	41	44	8	294	0.0316	46
2 bedrooms	41	24	3	148	0.0305	358
3 bedrooms	55	27	2	306	0.0298	1884
4 bedrooms	71	31	-1	282	0.0296	1470
At least 5 bedrooms	87	40	8	344	0.0301	465
Not specified	71	30	8	107	0.0290	9

* Only 1946 respondents provided income data.

Table 3. OLS regression results: Gross margin

Variable	Coefficient	Std. Err.
Age of respondent		
Aged 18-25	3.972	10.043
Aged 26-35	-3.890	2.156*
Aged 36-45	-2.179	1.712
Aged 46-55 (ref)		
Aged 56-65	2.058	2.067
Aged over 65	7.279	3.035**
Household income		
< €15,000	3.244	2.678
€15,000 - €30,000	2.517	2.021
€30,000 - €50,000	2.046	1.603
€50,000 - €75,000 (ref)		
> €75,000	1.750	1.785
Employment Status		
Employee (ref)		
Self-employed with employees	10.224	2.588***
Self-employed without employees	6.570	2.407***
Unemployed seeking work	0.117	3.952
Unemployed not seeking work	1.959	4.726
Retired	-0.451	2.807
Carer	7.490	8.156
Education level of CES		
No formal education	-1.398	6.025
Primary education	-2.135	2.696
Junior Certificate	-3.013	1.974
Leaving Certificate	-0.588	1.492
Third level (ref)		
Social Status		
AB: Managerial, administrative, professional	4.677	2.376**
C1: Supervisory or clerical, junior managerial, administrative or professional	2.111	2.108
C2: Skilled manual workers	2.112	2.266
DE: Semi and unskilled manual workers, casual workers, those in receipt of state benefits (ref)		
F: Farmers	-8.548	4.281**
Gender of respondent		
Male (ref)		
Female	0.086	1.255
Accommodation Type		
Apartment	-10.990	5.075**
Semi-detached (ref)		
Detached	4.037	1.670**
Terraced	-2.353	2.047
Not specified	3.504	1.701**
Tenure		
Renting Privately	-4.660	5.128
Renting from local authority	3.877	3.931
Owned outright (ref)		
Mortgage holder	2.204	1.494
Other tenure	22.991	26.206
Number of bedrooms		
1 bedroom	18.483	6.895***

2 bedrooms	-0.227	2.589
3 bedrooms (ref)		
4 bedrooms	3.698	1.495**
At least 5 bedrooms	13.720	2.246***
Type of Coker		
Electric Cooker (ref)		
Gas cooker	0.437	1.434
Oil fired cooker	3.062	3.933
Solid fuel cooker	0.685	4.737
Continuous Variables		
Number of electrical appliances	2.747	0.231***
Year accommodation was built	0.000	0.000
Number of household members	6.466	0.491***
Number of household members at home during the day	-0.252	0.162
Energy Conservation dummy variables		
External wall insulation	-3.400	1.339**
Attic insulation	-3.035	1.273**
Lagging jacket	-3.717	1.663**
Concerned about the environment	-0.948	2.372
Constant	-25.595	6.942***
Number of observations	1942	
Prob > F (47, 1894)	0.0000	
R-squared	0.3826	
Adj R-squared	0.3673	
Root MSE	25.901	

Figure 1. Average household electricity demand by time of day in 2009

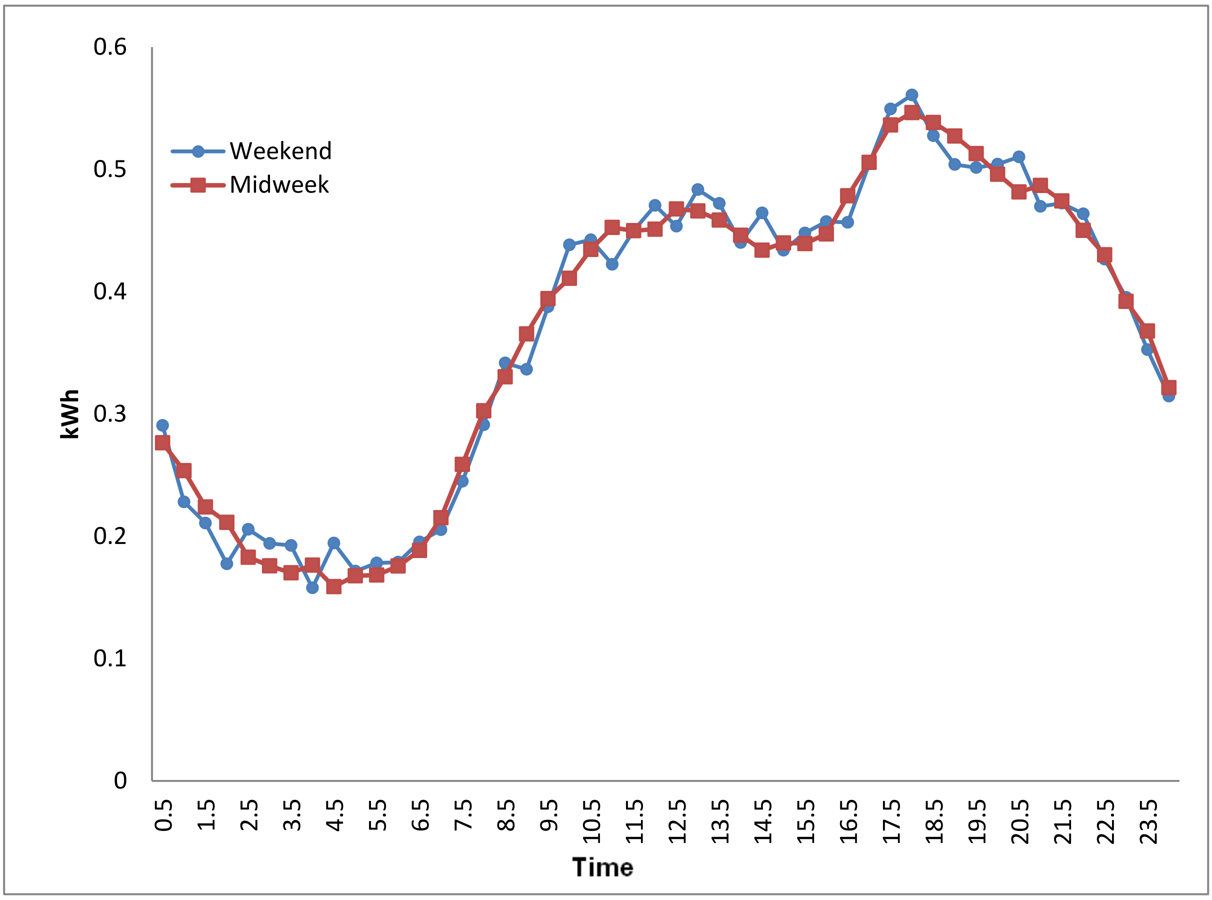


Figure 2. Average SMP by time of day in 2009

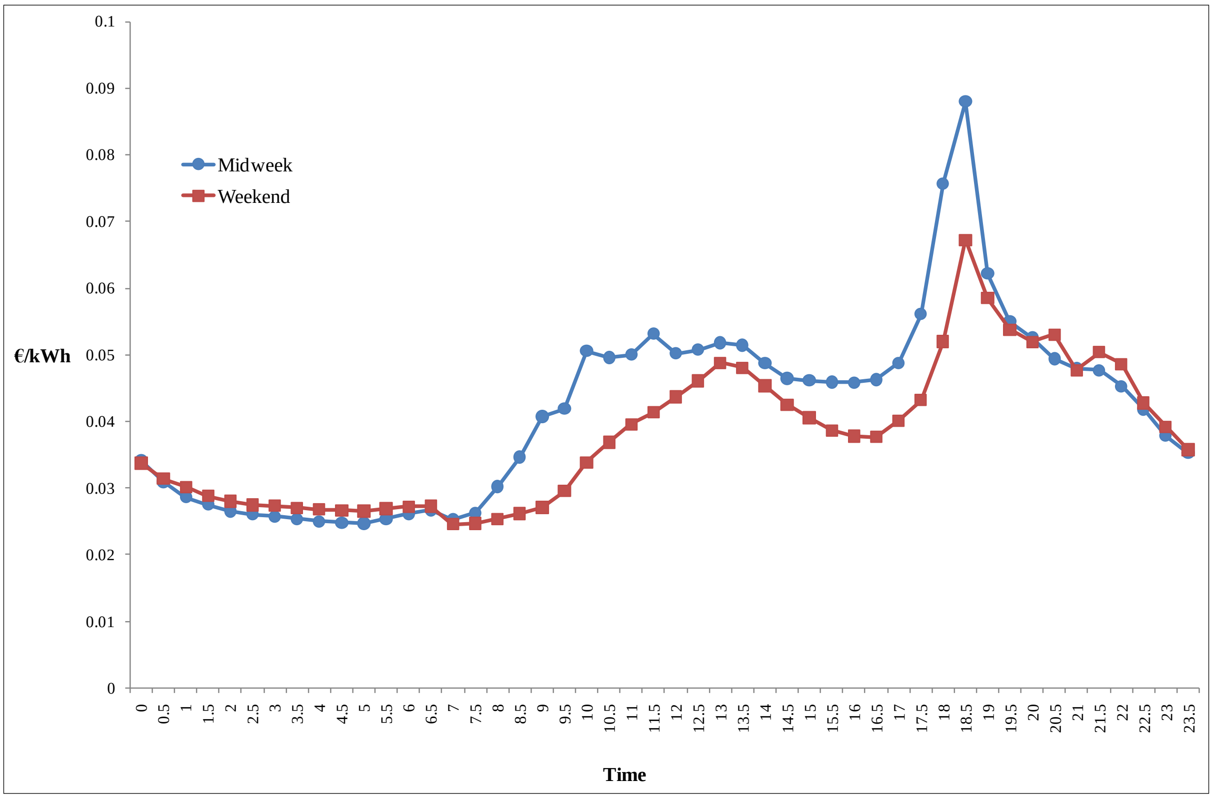


Figure 3A. Electricity profile by age group of respondent

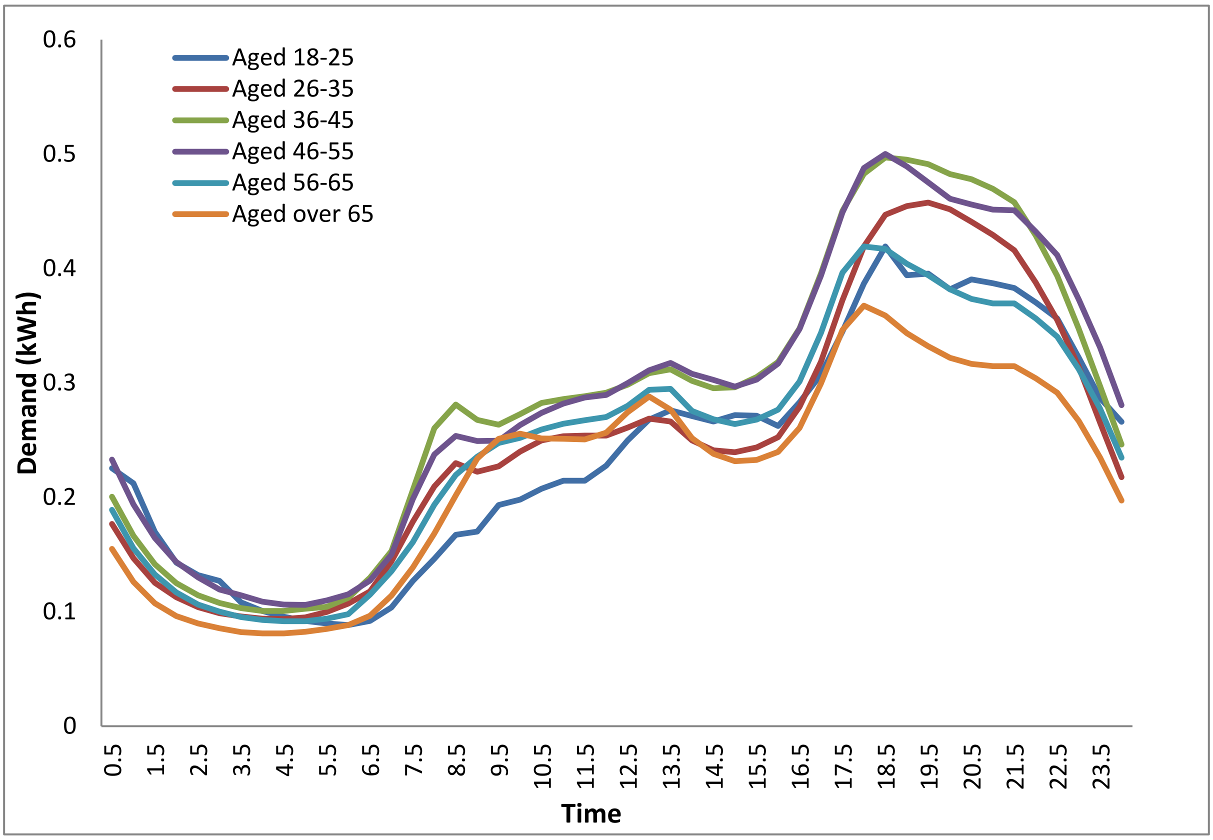


Figure 3B. Electricity profile by annual household income

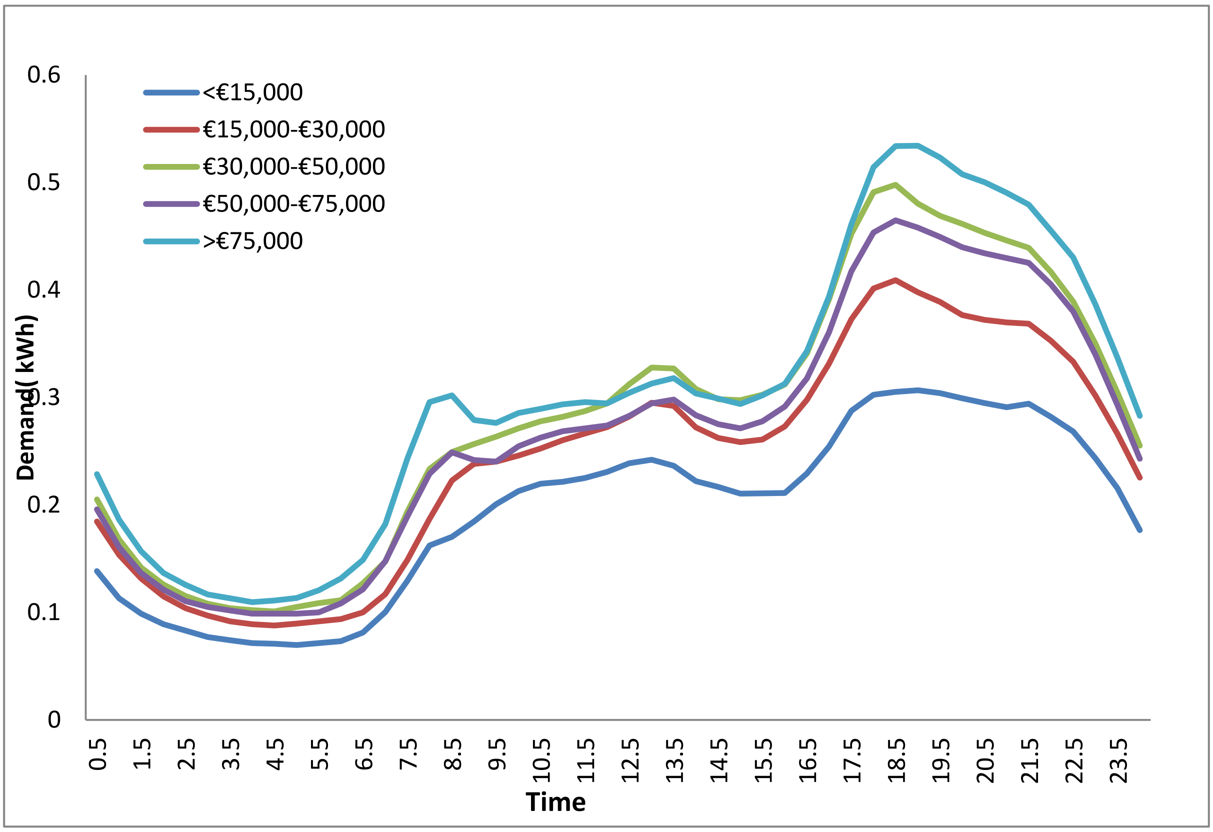


Figure 3C. Electricity profile by employment status of respondent

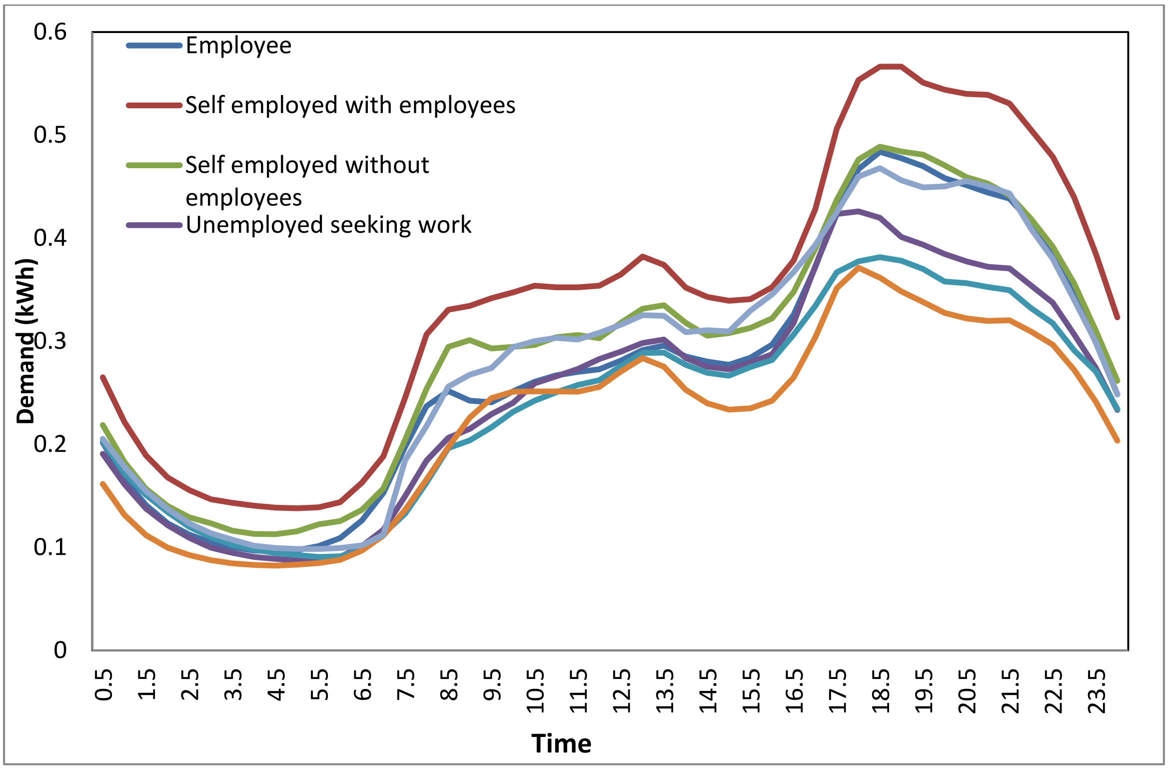
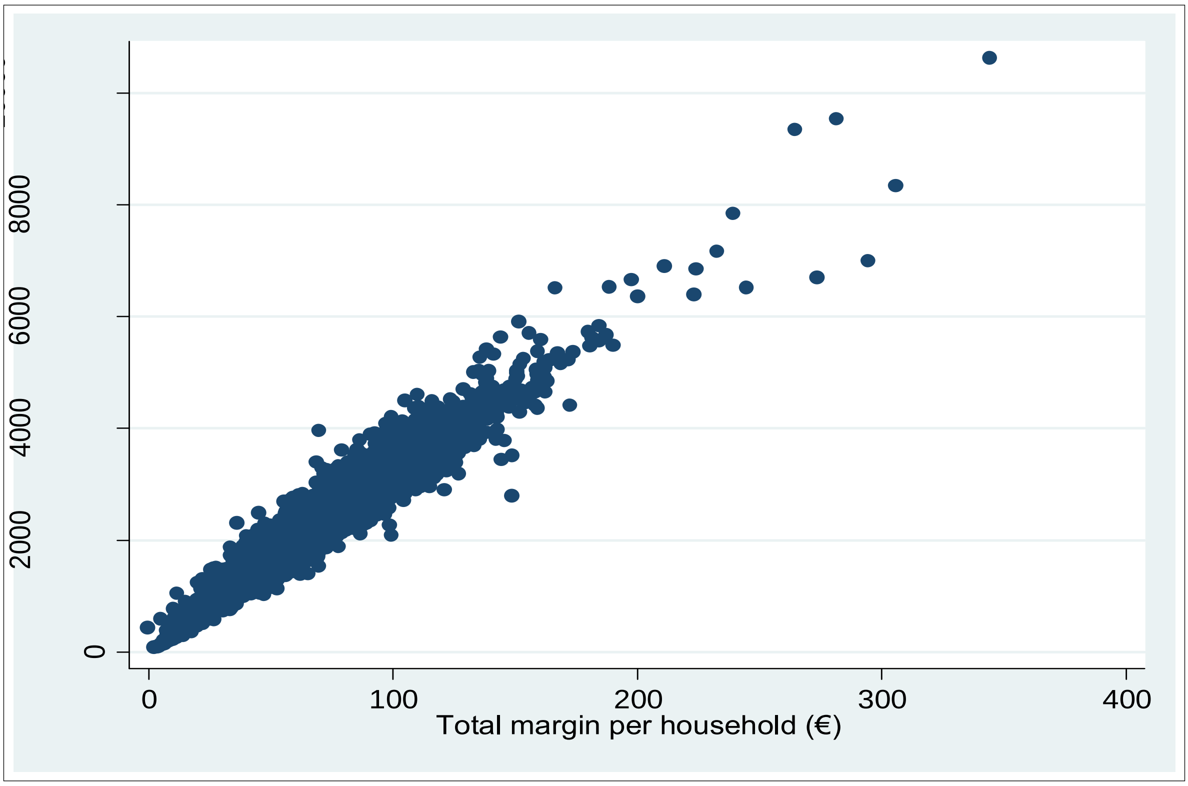


Figure 4. Total gross margin and total electricity demand



Appendix

Table A1. OLS regression results for all observations in the sample

Dependent variable: Gross margin

Variable	Coefficient	Std. Err.
Age of respondent		
Aged 18-25	-1.826	6.516
Aged 26-35	-5.059	1.563***
Aged 36-45	-4.267	1.219***
Aged 46-55 (ref)		
Aged 56-65	0.103	1.315
Aged over 65	2.902	1.778
Employment Status		
Employee (ref)		
Self-employed with employees	10.743	1.823***
Self-employed without employees	5.347	1.682***
Unemployed seeking work	-0.953	2.156
Unemployed not seeking work	2.903	2.354
Retired	1.662	1.707
Carer	7.409	4.185
Education level of CES		
No formal education	-0.195	3.483
Primary education	-2.899	1.478**
Junior Certificate	-1.396	1.227
Leaving Certificate	-3.595	1.015**
Third level (ref)		
Social Status		
AB: Managerial, administrative, professional	1.720	1.603
C1: Supervisory or clerical, junior managerial, administrative or professional	0.497	1.361
C2: Skilled manual workers	1.172	1.453
DE: Semi and unskilled manual workers, casual workers, those in receipt of state benefits (ref)		
F: Farmers	-7.099	2.775**
Gender of respondent		
Male (ref)		
Female	-0.032	0.815
Accommodation Type		
Apartment	-4.807	3.384
Semi-detached (ref)		
Detached	4.119	1.118***
Terraced	0.659	1.279
Not specified	4.388	1.123***
Tenure		
Renting Privately	-1.997	3.220
Renting from local authority	3.868	1.971**
Owned outright (ref)		
Mortgage holder	2.150	1.030**
Other tenure	6.802	7.818
Number of bedrooms		
1 bedroom	5.096	4.105
2 bedrooms	-3.745	1.586**
3 bedrooms (ref)		

4 bedrooms	4.430	1.009***
At least 5 bedrooms	12.844	1.503***
Type of Coker		
Electric Cooker (ref)		
Gas cooker	-0.065	0.944
Oil fired cooker	0.467	2.693
Solid fuel cooker	-0.443	2.825
Continuous Variables		
Number of electrical appliances	2.918	0.154***
Year accommodation was built	0.000	0.000**
Number of household members	6.167	0.323***
Number of household members at home during the day	-0.338	0.121***
Energy Conservation dummy variables		
External wall insulation	-1.415	0.878
Attic insulation	-2.385	0.850***
Lagging jacket	-0.676	1.092
Concerned about the environment	-0.372	1.561
Constant	-29.251	4.514***
Number of observations	4226	
Prob > F (47, 1894)	0.0000	
R-squared	0.3815	
Adj R-squared	0.3751	
Root MSE	25.683	