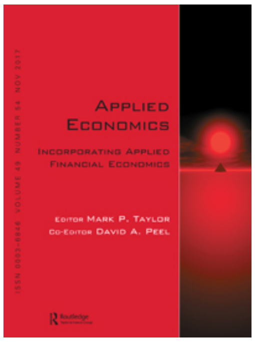

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The income elasticity of household energy demand: a quantile regression analysis

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ABSTRACT
This article examines variation in the income elasticity of household energy demand across the energy expenditure distribution using expenditure data from the five most recent Household Budget Surveys (HBSs) in Ireland: the 1987, 1994/1995, 1999/2000, 2004/2005 and 2009/2010 HBS. The analysis uses a two-stage instrumental variable quantile regression approach and is based on each HBS cross section, as well as the overall pooled observations. The estimated elasticities are compared across low- and high-energy-consumption scenarios and to a benchmark elasticity estimated using two-stage least squares. The results provide evidence that there is significant variation in the income elasticities across the energy expenditure distribution and that care must be taken when using the constant mean elasticity for policy purposes. More specifically, any examination of the future impact of a change in income support policy measures on energy consumption should recognize the substantial context-dependent variation in the income elasticity.

KEYWORDS
Household energy demand; income elasticity; energy expenditure distribution; quantile regression

JEL CLASSIFICATION
D12; D30; H31; Q41

I. Introduction

The main parameter of interest in the relationship between energy expenditure and income is the income elasticity of energy demand. This elasticity, which measures the percentage increase in energy expenditure given a 1% increase in income, is frequently used in models predicting future energy demand and for examining the effect of tax or subsidy policies affecting the residential sector. Examples of such policies include income support mechanisms and schemes to provide energy efficiency upgrades to dwellings, which aim to assist vulnerable households subject to fuel poverty. Moreover, for policymakers with an interest in reducing carbon emissions, the elasticity can be a useful parameter in estimating the effects of a carbon tax. In addition to these common uses, Sorrell, Dimitropoulos, and Sommerville (2009) explain that many studies provide elasticity estimates as proxy measures of the so-called rebound effect. The rebound effect arises where improved dwelling energy efficiency lowers the cost of using household energy goods and, therefore, results in an increase in household energy consumption. If energy efficiency measures are installed and this reduces the cost of energy such that a household's real income rises, then the income elasticity would measure the impact of a rise in real incomes on energy expenditure and, under certain assumptions, present a relevant proxy for the direct rebound effect.

It is generally assumed in the international literature that the effect on demand of a change in average income is the main concern and, as a result, the elasticity at mean income is usually the summary statistic of most interest when examining the relationship between energy expenditure and income. However, not all policy is concerned with the average and in most cases it is more likely to target low- or high-energy-consumption households. For example, the fuel poor are most likely in the lower left tail of the energy consumption distribution and are also primarily the target of income supports by policymakers. Therefore, the average effect of income on energy consumption given by the elasticity at mean income is of less relevance here, since the effect at the lower percentiles of the distribution is what matters to more accurately measure any policy response on energy demand. In other words, it is

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often important to recognize the context-dependent variation in the elasticity and to make use of the most applicable elasticity to the policy, in order to achieve a more accurate measurement of its impact on consumption.

Much of the international literature in this area focuses on the mean income elasticities for individual energy goods such as electricity or natural gas – see, for example, Asche, Nilsen, and Tveterås (2008); Baker and Blundell (1991) and Bernstein and Madlener (2011). However, there is also a limited body of this literature which has estimated the average income elasticity for total energy expenditure. For example, Meier and Rehdanz (2010) investigated household demand for energy in the U.K. using panel data over 15 years from 1991 to 2006 on over 5,000 households, and reported income elasticities ranging from 0.01 to 0.04 depending on the model specification. In examining household energy consumption in Norway for 1993–1995, Nesbakken (1999) estimated the average income elasticity of total household energy demand to be 0.01 and confirmed it to be stable across time. In a subsequent study, Nesbakken (2001) found the average elasticity of total energy demand to be 0.06 for Norwegian households and this represented an average across all heating systems. In general, the income elasticities in the international literature are very small, especially in comparison to those estimated in a number of Irish studies (see below). This is not surprising since the former generally control for the household's stock of energy-using appliances and a change in energy consumption as a result of a change in income can occur indirectly through a change in the stock of appliances.

Most of the Irish literature examining the relationship between energy expenditure and household income make use of the Irish Household Budget Survey (HBS) microdata sets and estimate the constant income elasticity of household demand for energy, for example, Conniffe (2000) considered the 1994–1995 HBS and reported the average income elasticity for household energy demand to be 0.32. More recently, Eakins (2013) found the average income elasticity of energy demand in the 1999 and 2004–2005 HBS to be 0.25 and 0.24, respectively. Furthermore, he reported that the elasticity is lower at 0.11 and 0.09 when the model controls for a range of other household and dwelling characteristics. Some Irish studies have also included other socio-economic characteristics as explanatory variables in modelling household energy demand, for example, Harold, Lyons, and Cullinan (2015).

Thus, within this context, it is clear that the literature concentrates solely on the average effect of income on household energy consumption rather than the effect across the energy consumption distribution. This article aims to fill this gap by examining the variation in the income elasticity of household energy demand across the entire energy expenditure distribution using a micro econometric analysis of energy expenditure data. To do this, we use data from Ireland, which have both appropriate microdata and a history of empirical work in income elasticities upon which we can draw. The data sets used are anonymized microdata files from five waves of a large-scale household expenditure survey: the 1987, 1994/1995, 1999/2000, 2004/2005 and 2009/2010 Irish HBSs. A two-stage instrumental variable quantile regression approach is applied to each cross section and the pooled observations to estimate elasticities across the distribution of energy expenditure. These elasticities are then compared across high- and low-energy-consumption profiles. In addition, a constant elasticity at the mean is estimated for all samples using a two-stage least squares (2SLS) method similar to that used in Conniffe (2000). This sets a benchmark elasticity to which the quantile elasticities can also be compared. The article provides evidence that there is significant variation in elasticities across high- and low-energy-consumption contexts and that some interpretative caution should be taken with regard to estimates from constant elasticity models.

The article proceeds as follows: the next section presents a detailed description of the data used in this analysis, while section III outlines the two-stage instrumental variable quantile regression methodology that is employed. The results of the analysis are presented in Section IV, while the final section concludes with a discussion around the policy implications of this work.

II. Data

This article uses anonymized microdata collected in five rounds of the Irish HBS, a survey of a representative random sample of all private households in Ireland which has been carried out periodically since 1951. The main aim of the HBS is to identify the pattern of household expenditure in order to update the weighting basis of the consumer price index. The survey involves participant households maintaining a detailed diary of household expenditures over a 2-week period together with collecting additional information on household facilities and sources of income. The rounds used here are for the years 1987, 1994/95, 1999/2000, 2004/2005 and the most recent 2009/2010 HBS. The analysis is conducted on all five rounds of the HBS and on the pooled sample of all observations across the five HBSs. The 1987 and 1994 HBS are converted to Euro using the fixed exchange rate of 1.27 at the introduction of the Euro and each individual cross section in the pool is inflated to 2009 prices.

The main variable of interest in the HBS for the purpose of this study is the expenditure under the subheading ‘fuel and light’. While expenditure on fuel and light includes many different energy goods such as candles and firelighters, energy expenditure in this analysis is taken to be any expenditure on electricity, natural gas, oil, coal, turf, anthracite, LPG, paraffin and wood. Another important variable in this study is total household expenditure. It is utilized as a proxy measure of household income and is determined by the aggregate of the expenditures in all 10 commodity groups within each HBS. These commodity groups are food, alcoholic drink and tobacco, clothing and footwear, fuel and light, housing, household non-durables, household durables, miscellaneous, transport and other expenditure.

Energy expenditure is the dependent variable in each cross section. The mean energy expenditure increased from €17.47 in 1987 to €35.12 in 2009, though when adjusted for inflation[1] it was relatively stable across the HBSs, ranging from a low of €31.36 in 1994 to a high of €35.70 in 2004/2005 (see Table 1). In each sample, total household expenditure is the independent variable of concern. Inflation adjusted mean total household expenditure increased from €518.27 in 1987 to €904.37 in 2004/2005 and declined to €809.37 in 2009, most likely due to the economic crisis of 2008 and the subsequent impact on consumer spending. Average energy expenditure as a proportion of average total household expenditure decreased over the period from 1987 to 2004/2005 with a slight increase in 2009. This provides some evidence that, post-crisis, household energy increased as a proportion of total household expenditure, which is expected from a good such as energy that is generally considered a necessity. For the pooled cross section, the mean energy expenditure was €34.30, while the mean total household expenditure was €742.66.

The focus of the analysis in this article however is on the entire distribution of household energy expenditure, as opposed to the just the averages. Therefore, Table 2 presents the deciles of energy expenditure across the individual HBSs and the pooled HBS sample, showing in all samples that energy expenditure is strictly increasing across the deciles. Moreover, Figure 1 presents a quantile plot of energy expenditure for the pooled HBS where the trend across the quantiles is much more observable. The quantile plot shows

Table 1. Mean total expenditure and mean energy expenditure by sample.

Year	Observations	Mean energy expenditure	Median energy expenditure	Mean total expenditure	Mean energy expenditure as a % of mean total expenditure
1987	7705	17.47	14.58	289.60	6.03%
1994	7877	19.31	17.68	395.85	4.88%
1999	7644	21.25	19.24	601.03	3.54%
2004	6884	29.91	26.96	841.15	3.56%
2009	5890	35.12	31.02	809.37	4.34%
Inflation adjusted:					
1987	7705	34.01	28.38	518.27	6.56%
1994	7877	31.36	28.72	579.31	5.41%
1999	7644	34.38	31.12	788.97	4.36%
2004	6884	35.70	32.18	904.37	3.95%
2009	5890	35.12	31.02	809.37	4.34%
Pooled	36000	34.30	30.60	742.66	4.62%

[1]Overall CPI: 1987 = 55.88, 1994 = 68.33, 1999 = 76.18, 2004 = 93, 2009 = 100. Housing and Fuel CPI: 1987 = 51.37, 1994 = 61.56, 1999 = 61.83, 2004 = 83.78, 2009 = 100. These represent the average monthly CPI across the months the relevant HBS was distributed.

Table 2. Deciles of energy expenditure by sample.

Decile	1987	1994	1999	2004	2009	Pooled
1	4.33	6.01	7.77	10.61	11.87	11.10
2	7.06	9.68	11.35	15.88	17.09	17.03
3	9.44	12.53	14.02	19.73	21.60	21.59
4	11.95	15.19	16.61	23.44	26.33	26.13
5	14.58	17.68	19.24	26.96	31.02	30.60
6	17.34	20.38	21.89	30.92	36.20	35.34
7	20.98	23.74	25.10	35.20	42.04	40.92
8	25.54	27.36	29.23	41.19	49.82	48.21
9	33.26	33.79	36.15	51.31	62.08	60.42

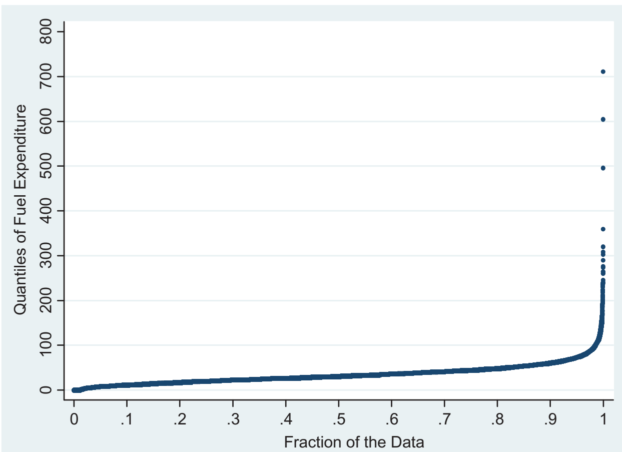

Figure 1. Q plot of fuel expenditure for the pooled HBS.

graphically the major quantiles of total household energy expenditure, where quantile q is an element of (0, 1) and is defined as that value of energy expenditure that splits the data into the proportions q below and (1−q) above. The plot indicates that the distribution of energy expenditure is concentrated in the lower left tail and is thereafter skewed to the right.

In the analysis, dummy variables are also added for the quarters over which the HBS microdata was collected in order to control for any seasonal changes in energy expenditures across the period taken to complete the survey. In terms of other explanatory variables, the categorical variable *deciles of household gross income* together with *social group* are also used as instruments for total household expenditure. Other socio-economic or household characteristics are not controlled for in this analysis. This is consistent with the previous Irish literature and implies that the estimated income elasticity includes both direct and indirect income effects, where the latter stems from a change in the household's stock of energy using appliances.

III. Methodology

The overall aim of this article is to examine the variation in the income elasticities of household energy across income deciles for both low- and high-consumption profiles. To begin, a semi-log model is used of the type specified in most of the previous Irish literature on energy elasticities and also advocated by Prais and Houthakker (1955). They suggest that while a double-log specification is better suited to luxury goods, the semi-log specification is a much better fit for necessity goods. Therefore, the model used here is represented as[2]:

$$X_i = \beta_0 + \beta_1(lnY_i) + \delta Q_t + \varepsilon_i,$$

where the dependent variable X_i denotes the energy expenditure of household i and Y_i is the total household expenditure of household i. Q_t are the quarter time dummies across the period of the HBS under consideration and ε_i is the error term. Conniffe (2000) explains that total household expenditure may be a better measure of true long-run income for two reasons. Firstly, income tends to fluctuate greatly over shorter periods, whereas expenditure is more likely determined by average income over the long run. Secondly, there is a tendency in surveys such as the HBS for some participant households to understate their incomes.

In order to set a benchmark, the model is first estimated for each HBS cross section and the pooled HBS cross section using an instrumental variable approach similar to that in Conniffe (2000). In order to correct for the endogeneity stemming from the association between fuel expenditure and total expenditure, total household expenditure is instrumented with the categorization by gross household income decile and by social group in a 2SLS estimation.

Following this, quantile regressions are also estimated to explore the variability in income elasticities across the distribution of energy consumption. In particular, the pth quantile regression estimators β_0^p, β_1^p and δ are chosen to minimize:

$$p \sum_{X_i \geq \beta_0^p + \beta_1^p Y_i + \delta^p Q_t} \left| X_i - \beta_0^p - \beta_1^p lnY_i - \delta^p Q_t \right|$$
$$+ (1-p) \sum_{X_i < \beta_0^p + \beta_1^p Y_i + \delta^p Q_t} \left| X_i - \beta_0^p - \beta_1^p lnY_i - \delta^p Q_t \right|,$$

where $0 < p < 1$.

[2]The analysis was also conducted using a linear and double-log specification and the semi-log specification was found to be a better fit.

Intuitively, a quantile p can be viewed as the point that minimizes the average weighted distance over the sample, where the weights depend on whether the point is above or below the value p. The weight is p for points above the fitted line and $(1-p)$ for points below. For example, in the case of median regression, where $p = 0.5$, which is also called least absolute deviations (LAD) regression, β_0^p, β_1^p and δ are chosen to minimize:

$$\sum_i \left| X_i - \beta_0 - \beta_1 ln Y_i \right|$$

Here, the weights are equal, so the quantile regression coefficients are estimated by minimizing the absolute deviations from the median and the regression line will pass through a pair of points with half the remaining data points above the line and the other half below the line. The quantile regression methodology is described in detail in Koenker and Bassett (1978) and Koenker and Hallock (2001).

In this analysis, quantile regressions are estimated at each decile for each cross section and the pooled observations, implying $p = 0.1, 0.2, \ldots, 0.9$. The coefficients are estimated using a quantile instrumental variable approach to correct for the endogeneity arising from energy expenditure being a direct component of total household expenditure. A similar methodology is outlined in Amemiya (1982) and it involves estimating a two-stage regression identical to 2SLS, though instead the first stage is an OLS regression and the second stage is a quantile regression.

The main parameter of interest is the income elasticity of energy demand, with the elasticity formula for the semi-log specification given by β/X. Benchmark elasticities are calculated at the mean energy expenditures (see Table 1) and the quantile elasticities are calculated at each decile of energy expenditure (see Table 2). Standard errors for the elasticities are obtained using a bootstrap methodology.

IV. Results

Table 3 presents the income elasticities of household energy derived from the benchmark 2SLS model and from the two-stage quantile models across the five HBS cross sections and the pooled cross section.

Table 3. Estimated income elasticities of household energy from the benchmark 2SLS model and the two-stage quantile models at each decile.

	1987	1994/1995	1999/2000	2004/2005	2009/2010	Pooled
Benchmark model						
2SLS	*0.32**	*0.28**	*0.25**	*0.25**	*0.33**	*0.28**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Two-stage Quantile models						
1	0.75*	0.79*	0.57*	0.63*	0.70*	0.69*
	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)	(0.02)
2	0.57*	0.52*	0.42*	0.43*	0.54*	0.49*
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)
3	0.48*	0.42*	0.35*	0.35*	0.46*	0.41*
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
4	0.42*	0.35*	0.32*	0.31*	0.43*	0.36*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
5	0.35*	0.31*	0.28*	0.28*	0.39*	0.31*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
6	0.31*	0.27*	0.25*	0.23*	0.36*	0.28*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
7	0.29*	0.23*	0.22*	0.21*	0.32*	0.25*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
8	0.27*	0.20*	0.20*	0.20*	0.29*	0.23*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
9	0.23*	0.16*	0.16*	0.18*	0.23*	0.19*
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)

Bootstrapped standard errors in parenthesis.
*Significant at 1% level.

Standard errors are bootstrapped with 500 replications. In terms of the results, the elasticity estimates vary over the period from 1987 to 2009 and they are all highly statistically significant. All the estimated elasticities are between 0 and 1 implying that the demand for household energy increases less than proportionately to income. Thus, household energy is income inelastic, confirming the finding in previous studies that the energy required to light and heat the home is a necessity good.

For the benchmark 2SLS estimates, the elasticity declines from 0.32 in 1987 to 0.28 in 1994/1995. Thereafter, it is steady at 0.25 across 1999 and 2004/05, with a large increase in 2009 to above the 1987 level at 0.33. A declining trend in the income elasticity of household energy demand is not unusual. It is explained by increases in the standard of living where households are equipped with central heating and a basic set of electrical appliances at a minimum. The rise in Ireland's income elasticity of energy in 2009 is therefore consistent with a fall in the standard of living following the economic crisis of 2008.

The variability of the income elasticity of energy demand across the distribution of energy expenditure is evident in all cross sections, with the elasticity ranging from 0.16 to 0.79 depending on the decile and cross section used. This variation is much more

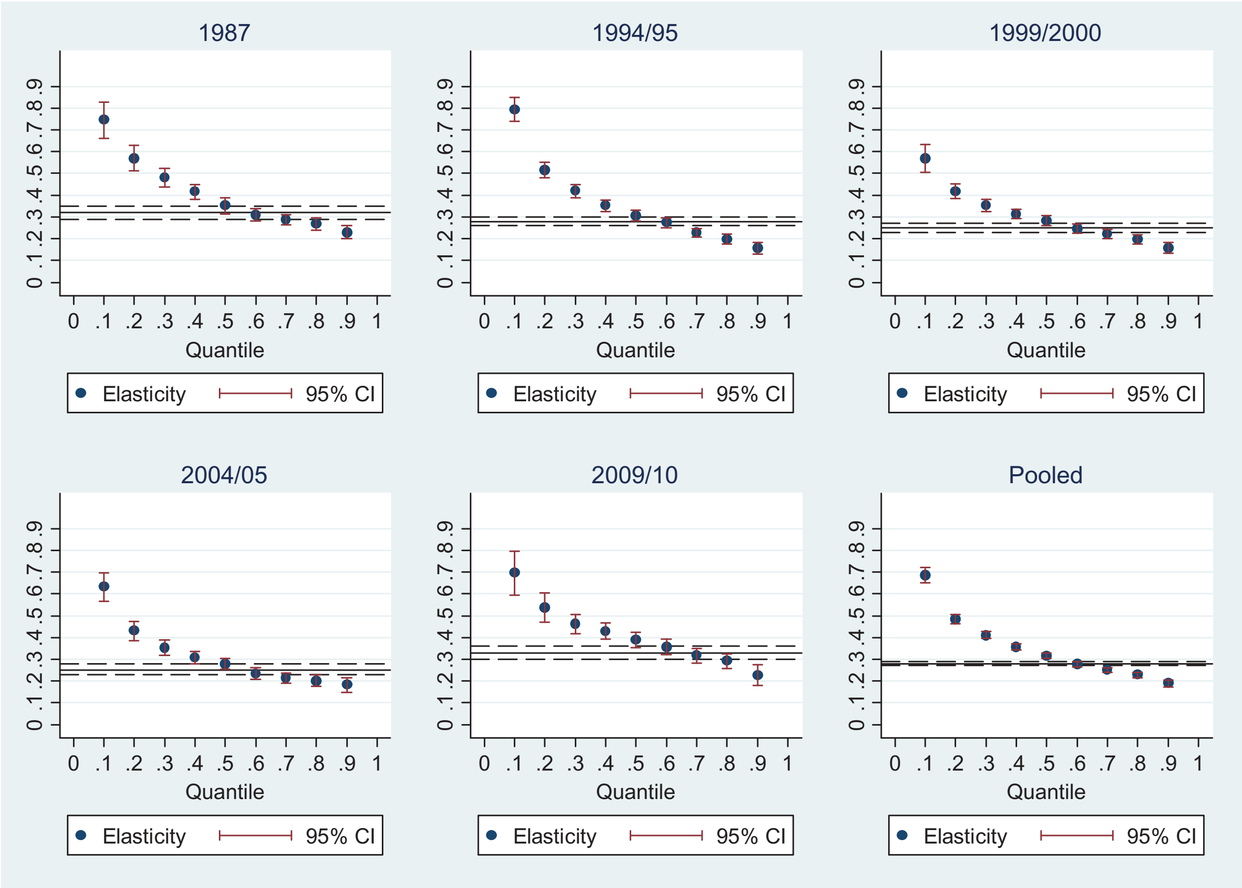

Figure 2. Graphs of estimated elasticity points and their 95% confidence intervals.

conveniently illustrated in the graphs in Figure 2. The graphs plot the elasticity points and their 95% confidence intervals for each of the quantile regressions from $p = 0.1$ to $p = 0.9$ over each HBS cross section. Each graph also shows the 2SLS estimate of the constant elasticity in the continuous black line together with its 95% confidence interval in the dashed line, allowing for a direct comparison to the benchmark elasticity. All the 95% confidence intervals shown are based on bootstrapped standard errors with 500 replications.

Comparing the income elasticity estimates across the whole distribution of energy expenditure, which is the main objective of this study, it is apparent that the absolute size of the elasticity is considerably larger for the bottom quantiles and smaller for the top quantiles in each cross section. The variation in the income elasticity is large with the elasticity likely to decrease as a household moves up the distribution of energy expenditure. As expected, low-energy-consumption households are much more sensitive to a rise in their incomes relative to high-consumption households.

To help illustrate the implications of this, Table 4 outlines a comparison of the estimated pooled elasticities in high- and low-consumption contexts, where the pooled cross section results offer an overall view of the variation in the elasticities. In considering the less extreme quantiles, such as the top 40% versus the bottom 40% of the energy expenditure distribution, the percentage difference in the income elasticity is a notable 29%. However, differences become much larger for the more distant quantiles, for example, the percentage difference in the elasticities between the top 10% and the bottom 10% is a very practically significant 263%. Differences are all statistically significant under the F-test at the 1% significance level.

In terms of comparison to the benchmark elasticity, differences are summarized in Table 5. With a skewed distribution, the median may become the more appropriate measure of central tendency.

Table 4. Comparison of the income elasticity of energy in high- and low-consumption scenarios for the pooled cross section.

Quantiles of energy expenditure distribution		% difference
(1)	**(2)**	
Top 10%	*Bottom 10%*	
0.19	0.69	263%*
Top 20%	*Bottom 20%*	
0.23	0.49	113%*
Top 30%	*Bottom 30%*	
0.25	0.41	64%*
Top 40%	*Bottom 40%*	
0.28	0.36	29%*

*Significant at 1% level.

Table 5. Comparison of quantile income elasticities of energy to the benchmark for the pooled cross section.

Benchmark	Quantiles of energy expenditure distribution	% difference
2SLS	*2SLAD*	
0.28	0.31	11%*
2SLS	*Bottom 10%*	
0.28	0.69	146%*
2SLS	*Top 10%*	
0.28	0.19	−32%*

*Significant at 1% level.

Therefore, median regression or LAD can be much more robust in such circumstances. The median (2SLAD) elasticity estimated for the pooled HBS (0.31) is slightly larger than the benchmark constant mean elasticity from the 2SLS estimation (0.28), with a percentage difference of 11%. Also, for the pooled cross section, the elasticity for the bottom 10% is almost 2.5 times the benchmark elasticity, while in contrast, the benchmark elasticity is about 1.5 times the elasticity for the top 10%. An important implication raised here is that the interpretation of the constant elasticity estimate needs to be treated with care, especially when it is used to advocate a policy which may target the left or right tails of the energy expenditure distribution.

V. Discussion

This article uses an econometric analysis of the household fuel and light expenditure data from the Irish HBS to examine the variation in the income elasticity of household energy demand across the distribution of energy expenditure. Household energy expenditure, together with some other socio-economic variables including total household expenditure as a proxy for income, are utilized from the 1987, 1994/1995 1999/2000, 2004/2005 and 2009/2010 cross sections of the HBS to conduct the analysis. A two-stage quantile regression approach with bootstrapped standard errors is undertaken to estimate the elasticities at all deciles in the distribution of energy expenditure for each cross section and their pooled observations. These elasticities are then compared across high- andlow-energy-consumption profiles and to a benchmark constant mean elasticity estimated using a similar technique to the 2SLS method outlined in Conniffe (2000).

The main finding is that there is a large variation in the income elasticity of household energy demand across low- and high-energy-consumption contexts. The absolute size of the elasticity is considerably larger for the bottom quantiles and smaller for the top quantiles across all cross sections with a percentage difference of 263% between the top 10% and the bottom 10% in the pooled cross section. This suggests that households with a low energy expenditure or located in the left tail of the distribution could be up to 3.6 times more responsive to a 1% increase in their income than households with high energy expenditure.

More specifically, there is a distinct difference between the benchmark constant elasticity estimate and the quantile elasticities. The bottom 10% in the pooled data is shown to have a 146% larger elasticity than the benchmark while the top 10% have a 32% smaller elasticity. This provides evidence that households with low energy expenditure are almost 2.5 times more sensitive to a 1% increase in their incomes than the constant mean elasticity would imply. This group is likely to include many households commonly classified as fuel poor.

The benchmark elasticities shown here are broadly consistent with other mean income elasticities in the literature. For example, Pratschke (1969) estimated the income elasticity for household energy demand to be 0.32 for the 1965–1966 HBS. For the 1987 HBS, Conniffe and Scott (1990) found the income elasticity of demand to be 0.43, though they applied a method which divided households into different groups and regressed group mean expenditures on group mean incomes. In a separate analysis, Conniffe (2000) considered the 1994–1995 HBS and noted that the income elasticity of energy demand when adjusted for the free electricity allowance is 0.25, an elasticity estimate confirmed by Eakins (2013) for the 1999 HBS also.

Similarly, in considering an alternative methodology and with electricity having the largest share in total household energy consumption, Curtis and Stanley (2016) employed almost ideal demand system models and identified that the income elasticity estimates for electricity vary between 0.29 and 0.84 for Ireland. Furthermore, and in an international context, the short-run income elasticities of residential electricity demand ranged from 0.04 to 3.48 with a mean of 0.28 in a meta-analysis conducted by Espey and Espey (2004). The benchmark total energy elasticity for the pooled model in this study is also an estimated 0.28.

Policymakers recognize household income as one of the main factors influencing the level of fuel poverty, together with fuel prices and the energy efficiency of the housing stock. Policy responses to fuel poverty can include the provision of income support and/or capital improvements to the energy efficiency of dwellings and equipment. The evidence provided in this article suggests that income supports could have a much greater importance for reducing the level of fuel poverty than previous research has suggested and is consistent with the finding that fuel poverty is primarily a matter of inadequate resources as reported by Watson and Maitre (2015). The energy expenditure of households located at the lower end of the energy consumption distribution, where the majority are most likely to be in fuel poverty, are much more sensitive to a rise in their incomes than the constant elasticity at the mean implies. Therefore, such households are benefiting greatly from income supports and such supports should help contribute to lifting them out of fuel poverty. Also, such transfer payments might be advocated given that there could be a 263% difference in the sensitivity of energy expenditure to an increase in income between the bottom 10% and the top 10% in the energy expenditure distribution.

The need to raise residential energy efficiency to advance climate policy goals is also a concern for many policymakers. Some countries subsidize energy efficiency schemes intended to deliver a range of energy efficiency measures for free or at reduced cost to vulnerable households. Our results suggest that if energy efficiency measures are installed in low-energy-consumption households and this reduces the cost of heating such that a household's real income increases, then the household could be more likely to maintain their expenditure on fuel and take the added benefit in additional heat. In other words, the rebound effect is likely to be much higher for low-energy-consumption households. These results lend support to the findings of both Murray (2013) and Chitnis et al. (2014) that the rebound effects are higher for low income households.

Publication bias has been highlighted as a concern in the estimation of the income elasticity of energy demand. Conventional wisdom implies that the income elasticity of household energy demand should be positive and therefore insignificant or negative estimates could be discarded, resulting in an upward bias in the overall literature. Funnel plots are a method of graphically testing for publication bias – see, for example, Havranek and Kokes (2015). The graph plots individual estimates of the income elasticity on the x-axis and the inverse of the standard error of the estimate on the y-axis, and so, the most precise estimates in the literature will be presented at the top of the funnel, while the less precise estimates will be more dispersed. A symmetric funnel is an indication that there is no publication bias in the literature. This article endeavoured to produce such a funnel plot including the benchmark elasticities estimated here. However, since the vast majority of the literature estimating income elasticities of total household energy demand does not report the standard errors of the elasticities, a reasonable funnel plot could not be produced. This, we suggest, is a limitation of the literature.

To conclude, allowing for a varying income elasticity of demand at different consumption levels shows significant variation compared to the mean elasticity. Policy analyses or forecasting models of residential energy use should take this substantial context-dependent variation in the income elasticity into account, particularly where the distributional effects of policy are of interest. Changes in income support measures, energy efficiency supports aimed at vulnerable households or indirect taxation of energy goods will likely produce very different outcomes than the mean elasticities might suggest.

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