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NECESSITY OR LUXURY GOOD?
Household Energy Spending and Income in Britain 1991-2007

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Abstract

The residential demand for energy is growing steadily and the trend is expected to continue for the foreseeable future. Household spending on energy services tends to increase with income. We explore household total spending on energy and on electricity and gas separately. We use an extensive British household panel data with more than 77,000 observations for the 1991-2007 period to explore the determinants of energy spending. We analyse income as a main driver of spending on energy and draw Engel spending curves for these. The lack of household level price data in liberalized retail energy markets is addressed by a new modelling approach to reflect within and between regional differences in energy prices. Also, long run changes in energy spending of households are approximated by exploring unit effects. The main results show the Engel spending curves are S-shaped. Income elasticities for energy spending are U-shaped and lower than unity, suggesting that energy services are a necessity for households. Moreover, the findings show that the income elasticity of energy spending is somewhat higher in the long run. Finally, we find a dynamic link between energy spending and income changes rather than a fixed budget threshold where basic needs are met. Hence, we suggest policy approaches that enable households to find their individual utility-maximizing energy spending levels.

Key words: Household energy spending, Engel, Price modelling

JEL Classifications: C23, D12, Q41

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1. INTRODUCTION

The residential demand for energy is growing steadily in line with the societies' increasing economic affluence. As a result, the household sector accounts for a significant and increasing share of total energy use and the economic welfare associated with this. The trend is expected to continue for the foreseeable future. Household spending on energy services tends to increase with income. Therefore, enhancing our understanding of the determinants and characteristics of household energy demand and spending is useful as an economic study as well as for policy analysis.

A distinctive economic property of energy demand by households is that this demand is not driven by the utility from the use of energy per se. Rather, energy is an indispensable input for utilizing a wide range of services provided by many appliances and devices. Hence, demand for energy is derived by the need for services required for a range of necessities such as heating and cooking, to leisure activities of normal and luxury nature and, more recently, for production purposes such as working from home.

As household incomes gradually increase, the household demand for and thus spending on energy tends to increase. However, the level and drivers of energy demand can change with income levels. The effect of an income increase can more than compensate that of a price increase as seen in the case of increasing demand for oil despite price rises in the mid-2000s. The rising energy price in recent years and expected future price increases, e.g. to finance energy and environmental policy objectives, will have important demand and welfare implications for households. While households with rising incomes may continue to increase their energy use and spending, those with low or stagnant incomes can be adversely affected by higher energy prices and expenditures. Waddams Price et al. (2007) show that households' perception of being fuel poor is linked to their actual fuel poverty.

A limited literature such as Baker et al. (1989), Yamasaki and Tominaga (1997), Liao and Chang (2002), Wu et al. (2004), Rehdanz (2007), Baker and Blundell (1991), Druckman and Jackson (2008), and Meier and Rehdanz (2008) have analysed aspects of household energy demand and spending. However, there is a need for further detailed studies of the underlying dynamics of household spending on energy in particular with respect to income changes and energy price differences among them. The drivers and determinants of demand for energy include a varied set of socio-economic factors ranging from income, through housing characteristics and family size to price responsiveness.

This paper differs in few respects from previous studies that use household production frameworks (Baker et al., 1989) or a discrete continuous approach (e.g. Baker and Blundell, 1991). The use of household micro data often requires the researcher to control for the effect of unobserved heterogeneity. We use an extensive real panel data of British household surveys that allows in-depth analyses of energy spending and income of the same households over time and control for the individual effects. This enables us to use fixed effects models to analyse the dynamics at the individual level while other studies have used pooled cross section data (Baker and Blundell, 1991; Baker et al., 1989; and Rehdanz, 2007). We take into account the temporal variations in energy spending and its time-varying determinants to capture the fixed effects as well as the socio-economic characteristics that affect energy spending. While previous studies have used cross-sectional data to analyse long-run responses to changes in income and price, the present paper also focuses on short-run responses to these. Moreover, Blundell et al. (2007) explore Engel curves for British family expenditure using semi-nonparametric techniques assuming that total budget is endogenous and households choose whether to spend their budget on goods or save instead. However, the choice between consumption and saving can be invariant over time. Using fixed effects models allows us to take a possible endogeneity into account.

In this paper, we analyse overall energy spending, as well as gas and electricity spending separately. The study covers the post-liberalisation period of the electricity and gas sectors in the UK after these transformed into market-oriented sectors. We focus on two aspects of household energy spending. First, we model the link between energy spending and income while controlling for a set of important variables. Some evidence suggests that energy spending tends to increase with income though less than proportionately (OECD, 2008) implying that, energy services may be regarded as a necessity good and have an income elasticity greater than zero and smaller than unity. We derive the Engel curves for energy spending holding other variables constant and provide evidence of a monotonic relationship between energy spending and income that suggests changes in the uses of energy as income increases. We show how energy spending changes as income (and prices) rises.

Second, we model the measurement errors in energy prices. Data on energy prices is only available as time series. This poses a challenge for empirical applications in liberalized energy markets where different households can be faced with differing prices depending on payment methods and region of living. Hence, the assumption that all households face identical fuel prices every year does not strictly hold. We address the lack of information in prices by modelling the difference between individual (i.e. household) and national prices as a function of differences in income with respect to households' own regions as well as the differences between regions. This approach aims to take into account that payment methods and location can yield different fuel prices for households with different income levels.

We find that the link between energy spending and income cannot be explained by simply describing energy as a necessity. Energy spending can increase with income, but at an uneven rate. Engel curves for energy spending are neither linear nor do they continuously increase or decrease. Rather, they exhibit an S-curved shape along which households energy spending increases, stagnates, or declines with income. We then show that income elasticity of energy spending changes with income. The results indicate that our modelling approach to overcome the lack of individual price data is effective. Also, the building types have significant impacts on energy spending. Moreover, energy spending increases in the number of children but decreases in the average household age. In addition, households with no access to gas tend to pay more for electricity. Finally, the second stage estimations indicate that household energy spending responds more strongly to changes in income in the long run.

The next section gives a review of the relevant literature. Section 3 describes the methodology used in the paper. Section 4 describes the data used and Section 5 presents and discusses the results of the empirical analysis for electricity, gas, and energy. Section 6 is the conclusions.

2. Previous Studies

The study of the link between income and household energy spending can be traced to the late 1800s. Engel (1895) analysed costs of living among Belgian working families. He stated that the welfare of a society depends on the extent to which its needs can be satisfied. Engel also argued that the income of a population must, at least, be high enough to cover its needs and thus its costs of living. He grouped these needs into different categories and suggested that not all needs are equal in terms of necessity and some goods and needs are important for physical survival, i.e. food, clothes, homes, health care, heating, and lighting. According to Engel, the level of social welfare depends on the ratio of spending on necessary goods over the budget remaining for spending on other goods. For spending on heating and lighting, Engel found that this accounted for 5% of total cost of living of a Belgian household.

Residential energy use has been the subject of other early studies and econometric analyses prior to the oil price shocks in the 1970s. In an early work Houthakker (1951) examined British urban electricity consumption. A number of other studies have since been undertaken. Madlener (1996) presents a detailed survey of the early literature (1951-1996) focused on studies of demand for electricity. The survey points to the difficulty of comparing the findings of many of the studies as they use a range of approaches and techniques.

In a study aimed at developing budget standards, Bradshaw et al. (1987) present the 'S-curve analysis' as a statistical technique to identify expenditure levels that could serve as such standards. They discuss the S-curve approach as a mean to detect inflection points where the expenditure allocated to a necessity good such as energy, food, and clothing turns. In other words, as household income increases, spending on necessity goods increases (less than proportional) until an inflection point is reached beyond which spending flattens (or even declines) before it increases again. The inflection points can shed some light on the nature of the consumption of a good as a necessity, normal, or for luxury use.

Whereas some empirical studies that followed Engel (1895) found considerable nonlinearities in Engel curves, recent studies in Bierens and Pott-Buter (1990) and Lewbel (1991) have advocated using nonparametric regression methods. Some studies control for measurement errors and other covariates, including Hausman et al. (1995) and Banks et al. (1997) who find that Engel curves for some goods display considerable curvature, including quadratics or S shapes.

Yatchew (2003) adopts a semi-parametric approach to estimate Engel curves for food using South African data. The study shows that food spending decreases in total expenditure. He also estimates equivalent scales for different family compositions or sizes in order to examine whether or not equivalence scales vary with income levels.[2] The results show that

[2] Equivalence scales model the dependence of utility functions on family size and use this dependence to compare welfare across households, assuming that a large family with a high income is as well off as a smaller family with a lower income if both families have demands that are similar in some way, such as equal food budget shares or equal expenditures on adult goods such as alcohol.

a couple with two children is equally well off relative to a single person household at an equivalent scale of 2.16. A parsimonious specification of equivalent scales produced lower standard errors than a pairwise comparison of Engel curves.

Blundell et al. (2007) explore Engel curve systems for the British Family Expenditure Survey using semi-nonparametric techniques. The study assumes that the total budget is endogenous and households choose whether to spend their budget on goods or save instead. However, the choice between consumption and saving is likely to be invariant over time. Using a fixed effects model as in our paper allows us to take this endogeneity into account. The study finds some evidence of an S-shaped relationship between income and consumption of different goods. They also explore the budget share spent on fuel for households with and without children. The Engel curve for fuel exhibits an almost continuously downward slope. Specifics of fuel consumption and what fuel actually stands for are not discussed in detail.

Baker et al. (1989) develop a two stage budgeting model of fuel consumption and explore households' response to price changes and response by different age groups and birth cohorts. The model assumes that, in the first stage, households allocate their income as budget shares to fuel consumption and non-fuel goods. In the second step, households make within-fuel decisions and allocate their fuel budget among different fuels. They control for some socio-economic characteristics for three income groups: lower, middle and top income deciles. The results indicate that gas and electricity are necessities and for some households, electricity is an inferior good.

Nesbakken (1999) analyses household energy consumption in Norway using a discrete choice model. The study explores the choice of heating equipment and models the residential energy consumption as being conditioned by the equipment. Income and energy prices are analysed for households with incomes below and above the mean level. The results show that short run income elasticities are equal to unity and hardly depend on income group. In the long run, low-income households have an elasticity of 0.18 and high income households have an elasticity of 0.22. Households in the high-income group had a higher price elasticity of energy consumption than low-income households. The higher price responsiveness of high-income households is explained by their high energy consumption and comparably lower marginal utility from energy consumption. In contrast, low-income households face larger loss of utility if energy prices increase and thus do not reduce their energy consumption to the same extent as high-income households.

Roberts (2008) focuses on low-income households in Britain and shows that some have a relatively high energy use and this is, in particular, the case for many elderly people who live in large and thermally inefficient homes. Druckman and Jackson (2008) analyse UK household energy use at national and local level using data from the Expenditure and Food Survey 2004-2005. The study uses the Local Area Resource Analysis (LARA) model to estimate household energy use in specific neighbourhoods. Socio-economic and demographic characteristics of households are viewed as important drivers and the findings show a strong link between energy consumption, income, and carbon emissions. Waddams Price et al. (2007) examine fuel poverty and its official definition in the UK. Using survey data of low income households the study examines the relationship between the objective fuel poverty measure and the attitude of households including their belief in the extent to which they can afford sufficient energy. The study shows that the households' perception of being fuel poor is linked to their actual fuel poverty.

Navajas (2009) explores the correlation between income and the natural gas consumption among Argentinian households and shows that at low prices, income only has a weak impact on consumption. At the same time, household characteristics such as the size of households are stronger drivers of gas consumption. In addition, some studies have explored other socio-economic and technical factors and their impact on energy usage and spending, for example, ageing households (Yamasaki and Tominaga, 1997 and Liao and Chang, 2002), tenancy of a property (Rehdanz, 2007 and Meier and Rehdanz, 2008), or technical characteristics of buildings (Leth-Petersen and Togeby, 2001).

The UK household energy consumption increased by 12% between 1990 and 2006 mainly due to an increase in the number of households and a trend towards smaller households. Currently, the domestic sector accounts for about 30% of UK's total energy consumption (Utley and Shorrock, 2008). In recent years the energy policy debate is increasingly influenced by climate change and renewable energy objectives both of which highlight the importance of improving energy efficiency (BERR, 2008; DTI, 2007). Residential energy usage has important social welfare dimensions that need to be taken into account in the current debate.

In the UK, households that spend more than 10% of their income on energy are defined as being fuel poor. These households are likely to face difficulty in warming their homes adequately. In addition, a comparatively lower share of their income can be spent on other goods (Defra and BERR, 2008). The climate change concerns and renewable energy policies will lead to higher energy prices. While the energy efficiency of the domestic building stock has improved considerably, the potential for further improvement remains high (DEFRA, 2009; Utley and Shorrock, 2008). This is also discussed in the Hills (2012) report that argues that instead of focusing on percentage income thresholds as an indicator for fuel poverty, individual households should be explored instead. According to the report many fuel poor households are on low income and live in houses that can only be warmed at very high costs.

3. Methodology

As noted previously, some studies that have explored the link between energy usage and income have found positive income elasticities lower than unity. All studies tend to estimate a single value for income elasticity for a whole sample or some sub-groups. However, the dynamics behind the link can be better analysed using a panel micro-dataset while controlling for other socio-economic variables. In this paper we explore the linkage between household energy spending and income as well as the differences among fuels.[3]

[3] We do not explore the linkages between spending on different fuels and hence do not use spending shares as in Baker et al. (1989).

Following Bradshaw et al. (1987) and Jamasb and Meier (2010), we derive a plot of average energy spending against average income levels in Figure 1 for the period of study (1991-2007). As can be seen from the figure, energy spending tends to continuously increase in income even though at certain income levels energy spending stagnates (or even declines) as income continues to increase. However, the standard deviations show that this link is rather complex and other variables can have an impact on energy spending at differing income levels. In order to understand this link we use econometric models that enable us to control for the impact of other factors and thus draw a more differentiated picture.

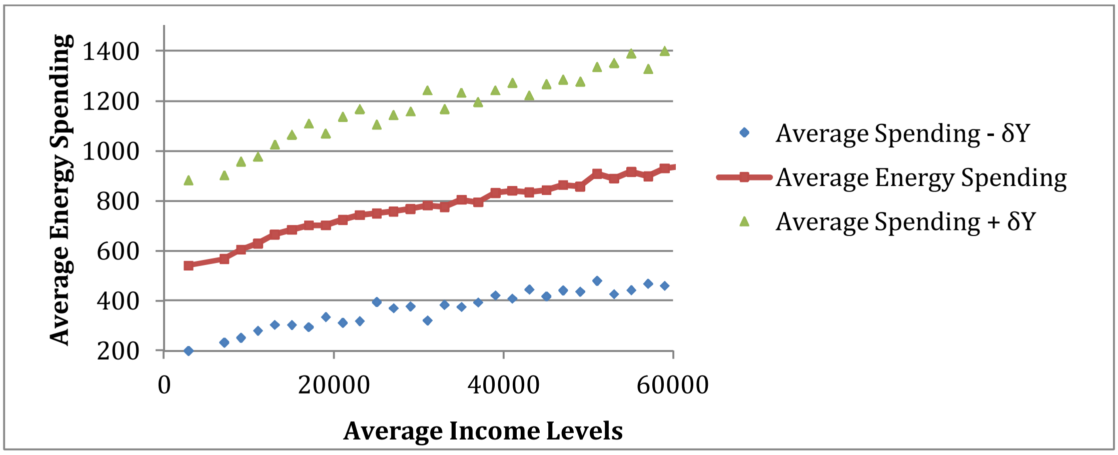

Figure 1: Average energy spending levels and standard deviations for average gross household real income levels

We examine total energy expenditures as well as spending on electricity and gas, separately using an econometric analysis of a large sample of households in Great Britain. We model third-order functions of income in order to examine spending response to income changes. Understanding the dynamics of how energy spending changes with income is helpful for designing targeted policy measures. Further, we address measurement errors in fuel prices as households in a liberalised retail markets face different energy prices for which data is not available.

We specify a set of econometric models of income, fuel prices and other determinants of energy spending in order to draw Engel curves for energy spending as well as for spending on electricity and natural gas separately. We utilize the panel nature of the data in order to control for the effect of unobservable effects, in our case, individual household characteristics, that influence their energy spending. Our energy spending models can be generalised as in Equation (1).

$$\ln E_{it} = X_{it}\beta + v_i + \epsilon_{it} \tag{1}$$

where $\ln E_{it}$ is overall energy, electricity, or natural gas spending in logs, subscript i=1,…,N stands for household, subscript t is time, X_{it} is a vector of explanatory variables, v_i captures cross-sectional heterogeneity in our dataset, and ε_{it} is the conventional noise term.

Some studies have used different estimators with panel data models (e.g. Sherron and Allen, 2000; Farsi and Filippini, 2004; Hausman and Taylor, 1981) where the debate on model specification has mainly focused on the fixed versus the random effects approaches. Random effects (RE) models capture the effect of individual differences but these are treated as random as opposed to parameters estimated using the fixed effects approach (FE). The random effects models assume that the time-invariant household characteristics are randomly distributed across households but they are uncorrelated with the explanatory variables. If this assumption holds, the random effects approach leads to more efficient estimation results. However, if the assumption is incorrect, it leads to biased results.[4]

We test whether the random effects and the explanatory variables are correlated using the Hausman test of the hypothesis that differences in coefficients are not systematic. The test calculates the differences between the coefficients of fixed effects and random effects models and examines if the coefficients vary systematically. The null hypothesis is the lack of correlation and hence that the RE coefficients are estimated consistently. In our analysis the Hausman test rejected the random effects model. Hence, we use the fixed effects approach to estimate our models. The results of the Hausman tests are presented in Section 6.

Also, as the household effects are correlated with the explanatory variables[5], we can use the traditional fixed effects estimator to address the endogeneity problem. As this estimator ignores the cross-sectional (i.e. between) information among households and only takes into account the temporal (i.e. within) dimension of our data, it is not possible to control for time-invariant variables. However, the inability to control for time invariant variables is not hindering our analysis as the variables used in our models vary over time.[6] An extension of the Hausman test is the Sargan-Hansen test. A cluster-robust version of this test is robust to heteroskedasticity as well as within-group correlation (Schaffer and Stillman, 2010).[7]

As mentioned, the models used in our analysis have two important features. First, we use third-order functions of income in order to identify inflection points in “pure” Engel energy spending curves. Hence, our model in equation (1) can be rewritten as:

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[4] See e.g. Hausman (1978), Owusu-Gyapong (1986), Baltagi et al. (2003), and Hausman and Taylor (1981).

[5] The household effects might, for example, cover the environmental attitude of household members. An environmental-friendly attitude could lead to more efficient energy usage due to, for example, differences in education levels which also affect income levels.

[6] While fixed effects models make weak assumptions on the unit-specific effects, in that they can be arbitrarily correlated with the regressors, and have the virtue of being relatively easy to implement, they produce imprecise estimates when the data contains variables with relatively low within variance.

[7] The test is run using the ‘xtoverid’ Stata command by Schaffer and Stillman (2010). Using the cluster option, the test is robust to heteroskedasticity and within-group correlation. The test shows whether the extra orthogonality conditions used in the random effects estimator are valid, i.e. both ‘FE’ and ‘RE' estimators would be efficient. If the null hypothesis is rejected, the random effects estimator is inconsistent.

$$\ln E_{it} = \ln f\,(Y_{it}, \alpha) + X_{it}\beta + v_i + \epsilon_{it} \tag{2}$$

where Y_{it} is annual household real income, and *f(·)* is a third-order function of income and can be interpreted as a "pure" Engel energy spending curve. We use the following cubic functional form for *f(·)*:

$$\ln f\,(Y_{it}) = \alpha_1 \ln Y_{it} + \frac{\alpha_2}{2}(\ln Y_{it})^2 + \frac{\alpha_3}{3}(\ln Y_{it})^3 \tag{3}$$

The second aspect concerns the energy prices. Disaggregated average energy prices are available on a regional level and for the main three different payment methods from the Department of Energy and Climate Change (DECC).[8] However, this data is only available for the 1998-2007 period and thus restricts the number of observations that can be analyzed.[9] Hence, we use both the annual price data for the UK reported in IEA (2005; 2007) as well as the between and within regional differences in income to control for the unobserved differences in prices among households. Our results support this approach.[10]

In liberalised retail electricity markets, the actual prices paid by individual households can vary somewhat around average annual prices reported by official statistics. Indeed, estimates of annual domestic bills show that unit prices do not only vary among the regions but they also vary with the choice of supplier and contract type. Also, some consumers can pay more than others if they do not take advantage of the competitive retail market. Although many consumers switch supplier, some only switch from one former monopoly to another former monopoly supplier. Nearly 70% of consumers still have their energy supplied from a former monopoly supplier (Ofgem, 2008).

Prices can also differ according to payment methods such as such as credit, direct debit, or prepayment. Evidence suggests that customers on direct debit payment have the lowest unit prices (DECC, 2011). Households on low incomes make up a large share of pre-payment users. Although these consumers generally pay higher unit prices, many of them choose this method in order to better manage their budget. In addition, price premiums for pre-payment meters can vary according to geographic region and the amount of energy consumed. Moreover, consumers on single-fuel arrangements pay higher margins due to the lack of competition. In

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[8] See http://www.decc.gov.uk/en/content/cms/statistics/energy_stats/prices/prices.aspx.

[9] Issues arising in this context are discussed in Section 5.

[10] Regardless of the data set, our *aggregated* price variables are crude proxies of the real average prices paid by *individual* households. This obviously prevents computing energy quantities and estimating a pure energy demand function. It is worth mentioning that average prices paid by individual households will vary with quantities consumed as tariffs are decreasing in quantities. The lack of individual information on prices does not allow us to address this issue explicitly. However, our empirical model is able to capture this issue indirectly. Households on higher incomes tend to use cheaper per unit payment methods than poorer households. Thus individual average prices (which are not observed by the researcher) will be correlated with income. As explained later on, we address this endogeneity problem by adding two variables measuring *within* and *between regional* differences in income. At the same time, since individual average prices are unobserved, some of the variation will be captured by the fixed effects in our model.

Scotland and Wales markets are more concentrated and a large number of rural consumers is not connected to the gas grid and pays higher premiums on their electricity prices (Ofgem, 2008).

There are three main drivers of differences in prices among households: market concentration, the payment method, and single fuel arrangements. In order to control for unobserved differences in prices among households we incorporate proxies for these drivers in our model. First, there are variations in energy prices across the regions due to differences in market structures. We proxy the regional differences in prices by using the differences in income levels between different regions. The intuition behind this is that the more densely populated regions are also regions with higher Gross Disposable Household Income (GDHI). At the same time, in these regions, energy markets tend to be less concentrated, therefore there is a higher likelihood of consumers switching suppliers and hence price margins being lower. For example, London has the highest GDHI per head while Scotland and Wales have the lowest GDHI (ONS, 2009a) and also have the most concentrated energy markets in Great Britain.

Second, we control for the within-region differences in energy prices due to payment methods by including a variable that measures the differences in income levels within individual regions. As mentioned, households on very low incomes make up the largest share of the prepayment consumers and pay higher prices. For example, London has the highest GDHI among all GB-regions but it also has the most unequal distribution of incomes. A large number of households in London lives on very low incomes (ONS, 2009a). In order to address this issue, we model the differences in energy prices within the regions based on differences in income levels within regions. Third, households on single fuel arrangements who are not connected to the gas network tend to pay higher electricity prices (Ofgem, 2008). We control for this by assuming that households with no gas spending do not have access to gas.

If we remove fuel prices from the set of explanatory variables, the model to be estimated can be written again as:

$$\ln E_{it} = \ln f\,(Y_{it}, \alpha) + X_{it}\beta + \gamma \ln P_{it} + v_i + \epsilon_{it} \tag{4}$$

where P_{it} is the actual price paid by an individual household *i* in year *t*. It could be either the gas or electricity price or a vector of the two prices. Since actual prices paid by individual households are not available, we use the annual price data for the UK as reported in IEA (2005; 2007). As data on energy prices is only available as time series, we replace P_{it} by the average annual price, P_t, reported by official price statistics, for all households. This implies that measurement errors in individual fuel prices occur and it can be modelled as:

$$\ln P_{it} = \ln\left(\frac{P_{it}}{P_{Rt}}\right) + \ln\left(\frac{P_{Rt}}{P_t}\right) + \ln P_t \tag{5}$$

where P_{Rt} is the average price in the household's region R, which is common to all households in region R. Hence, if we replace $\ln P_{it}$ in Equation (4) with the expression in (5), we obtain:

$$\ln E_{it} = \ln f\,(Y_{it}, \alpha) + X_{it}\beta + \gamma\left[\ln\left(\frac{P_{it}}{P_{Rt}}\right) + \ln\left(\frac{P_{Rt}}{P_t}\right) + \ln P_t\right] + v_i + \epsilon_{it} \tag{6a}$$

or,

$$\ln E_{it} = \ln f\,(Y_{it}, \alpha) + X_{it}\beta + \gamma \ln P_t + \gamma\left[\ln\left(\frac{P_{it}}{P_{Rt}}\right) + \ln\left(\frac{P_{Rt}}{P_t}\right)\right] + v_i + \epsilon_{it} \tag{6b}$$

where the term in brackets represents the measurement errors in individual energy prices*, i.e.* $\ln P_{it} - \ln P_t$. From Equation (5), the measurement errors in individual prices are decomposed into *within region* differences (i.e. the gap between the individual price and the average price in household's region) and *between region* differences (i.e. the gap between the average price in household's region and national energy prices). Both gaps within and between region differences are not observed, hence we proxy them using differences in income.[11] In particular, we model the errors in energy prices as follows:

$$\ln P_{it} - \ln P_t = \delta_W \ln\left(\frac{y_{it}}{y_{Rt}}\right) + \delta_B \ln(\frac{y_{Rt}}{y_t}) + \delta_A ng_{it} \tag{7}$$

In addition, we include a dummy variable for access to gas, ng_{it}, in order to capture the differences in prices due to lack of gas connection. If we insert (7) into (6b), the final model to be estimated is as in Equation (8):

$$\ln E_{it} = \ln f\,(Y_{it}, \alpha) + X_{it}\beta + \gamma \ln P_t + \theta_W \ln\left(\frac{y_{it}}{y_{Rt}}\right) + \theta_B \ln(\frac{y_{Rt}}{y_t}) + \theta_A ng_{it} + v_i + \epsilon_{it} \tag{8}$$

where $\theta_w = \gamma\delta_w$, $\theta_B = \gamma\delta_B$, and $\theta_A = \gamma\delta_A$. We estimate the effect of various independent variables on total energy spending, E_{it}, as well as the spending on electricity (E_{it}) and natural gas (G_{it}). We distinguish among these two energy sources as they are mainly used for different purposes. While electricity can be used for all electric appliances, gas is mainly used for heating and hot water supply. Total energy spending covers both effects and includes spending on oil which is also used for heating.

Based on Equation (8) our models for total energy spending with and without controlling for differences in individual and national prices are given in Equations (9) and (10).

$$\ln E_{it} = \ln f\,(Y_{it}, \alpha) + X_{it}\beta + \gamma \ln P_{gt} + \gamma \ln P_{et} + \theta_W \ln\left(\frac{y_{it}}{y_{Rt}}\right) + \theta_B \ln(\frac{y_{Rt}}{y_t}) + \theta_A ng_{it} + v_i + \epsilon_{it} \tag{9}$$

$$\ln E_{it} = \ln f\,(Y_{it}, \alpha) + X_{it}\beta + \gamma \ln P_{gt} + \gamma \ln P_{et} + \theta_A\, ng_{it} + v_i + \epsilon_{it} \tag{10}$$

The difference between those two equations is in the implementation of the measurement errors in individual energy prices ($\ln P_{it} - \ln P_t$). These are captured in (9) but omitted in (10). A comparison of the estimation results of the two models will reveal the differences in their

[11] An alternative approach is to treat the term in brackets as an omitted variable and leave it in the error term. As prices are measured with error, endogeneity problems might arise (see e.g., Wooldridge 2002), and an instrumental variable estimator should be used to consistently estimate the main coefficients of the energy spending function. However, as pointed out by Greene (2005), identifying appropriate instrumental variables in this setting is difficult. Unlike in other empirical exercises, and as discussed earlier, with our approach it is easier to find proxies for the measurement error term, lnP_{it}-lnP_t, than in an IV procedure. Using the latter approach, good instruments are variables that are *not* correlated with lnP_{it}-lnP_t, but highly correlated with the observed price, lnP_t.

explanatory powers. Note that in equation (10), we retain the no gas (NOGAS) dummy in both models because it is not related to specific regions but refers, to some extent, to the general rural vs. urban divide which is different from regional differences across the country. This can be related to the urban heat island effect which implies that heating loads of buildings tend to be lower in cities where a larger amount of buildings is built on a smaller area as opposed to rural areas (Kolokotroni et al., 2012). At the same time, the number of flats with lower levels of heat loss is higher in urban areas while there are more detached houses in rural areas.

Furthermore, Pg_t and Pe_t denote the annual gas and electricity prices, respectively. The vector of explanatory variables X_{it} reflects the socio-economic and building characteristics at the household level. The socio-economic variables are the average household age (AVERAGE AGE), the number of children (CHILDREN) as well as a dummy variable that is equal to one if a households owns the property (OWNED). Building characteristics cover differences in building types. These are dummies for detached (DETACHED) and semi-detached (SDETACHED) houses, end-terraced (END-TERRACED) and terraced (TERRACED) houses and flats (FLATS). The household specific fixed effects are given with v_i.[12]

We hypothesise that spending levels increase in fuel prices but decrease in within and between regional differences in income levels. For the explanatory variables we hypothesize that energy spending increases in average household age with older household members spending more time at home. We also expect energy spending to be increasing in the number of children. First, children tend to spent more time at home than a full-time working adult and second; the number of appliances tends to be higher for households with more children. When households own their home they have a stronger incentive to invest in the energy efficiency but they also tend to live to larger extents in detached and semi-detached houses and thus experience higher heat loss levels than renters who mainly live in flats.[13] For the building types we assume that flats have the lowest spending levels and detached houses the highest levels of all building types.

Regarding specific fuels, we estimate the following models for electricity and gas, respectively:

$$\ln EL_{it} = \ln f\,(Y_{it}, \alpha) + X_{it}\beta + \gamma \ln Pe_t + \theta_W \ln\left(\frac{y_{it}}{y_{Rt}}\right) + \theta_B \ln(\frac{y_{Rt}}{y_t}) + \theta_A ng_{it} + v_i + \epsilon_{it} \tag{11}$$

$$\ln G_{it} = \ln f\,(Y_{it}, \alpha) + X_{it}\beta + \gamma \ln Pg_t + \theta_W \ln\left(\frac{y_{it}}{y_{Rt}}\right) + \theta_B \ln(\frac{y_{Rt}}{y_t}) + v_i + \epsilon_{it} \tag{12}$$

[12] Using the 'Stata xtreg, fe' command, we assume that the average value of the fixed effects of all households is equal to zero.

[13] See Meier and Rehdanz (2010) for a discussion.

Here EL_{it} in (11) and G_{it} in (12) represent household annual electricity and gas spending, respectively. For the individual fuels we only control for the respective fuel price[14] and omit the no-gas-dummy in (12).

As noted earlier, the parameters of the above models can be interpreted as short-run responses in energy expenditures to changes in income and/or other explanatory variables. In particular, as from one year to another we do not expect major technological adjustments[15], the estimated vector of parameters α is mostly related to income variations over time, given the stock of appliances used. However, since the mix of appliances is related to income we also expect a different effect of income on energy expenditures for different levels of income. The short-term approach to modelling demand/expenditure has been used in other studies reviewed earlier - e.g. in Meier and Rehdanz (2010), Rehdanz (2007), and Leth-Petersen and Togeby (2001).

We use a log-linear functional form, i.e. we take the natural logarithm of energy expenditures, energy prices, annual household income and the number of children. Also, we use the Consumer Price Index (CPI) of the UK Office for National Statistics (ONS) with 2005=100 (ONS, 2009b) to adjust all monetary values to overall price developments. Thus, the dependent variables are the ln of household annual electricity, gas, and energy expenditures in 2005 prices.

4. DATA

The data used in this study is based on the British Household Panel Survey (BHPS). The dataset consists of an unbalanced panel of more than 5,000 households, over a 17 year period from 1991 to 2007. As part of the survey approximately 10,000 individuals have been re-interviewed annually. The primary objective of the survey is to enhance understanding of social and economic change at individual and household level in Britain. The BHPS covers the major topics of household organization, labour market, income, and wealth as well as housing etc. The survey is intended to be nationally representative. However, this may not be necessarily the case along the dimension of household income. The selection of households for the survey is based on a clustered stratified sample of addresses in Great Britain; and the main selection criteria are age, employment, and retirement.

The BHPS survey contains data on annual household spending on different fuels, information on buildings (building type, ownership of property), and regional location of households. It is also possible to differentiate between households living in urban and rural areas. In addition, the data includes annual household income as well as several household characteristics such as size, age of members, employment status. Table 1 presents the summary statistics for the

[14] As our dependent variables are spending levels rather than consumption levels the interpretation of cross price effects is not as straightforward. We expect electricity and gas in the short run to be mainly complementary and thus an increase in the price of electricity would reduce gas *consumption*, if both fuels are available.

[15] I.e. the FE estimator only takes into account the within-household annual (short-term) variations.

data and the models used in this paper. Except for the dummy variables we use the natural logarithm of all explanatory variables in our analysis.

Variable	Obs	Mean	Std. Dev.	Min	Max
ENERGY*	77,116	723.81	377.21	1.07	11,915.57
ELECTRICITY*	77,116	368.7	224.14	1.05	8,592.91
GAS*	67,941	375.62	227.07	0.96	11,171.38
INCOME*	77,116	26,293	21,339	76	764,801
INCOME SQ	77,116	49.35	7.52	9.35	91.77
INCOME TR	77,116	329.71	74.26	26.95	828.79
GAS PRICE*	77,116	243.42	42.83	207.89	359.71
ELECTRICITY PRICE*	77,116	0.08	0.01	0.07	0.1
INCOME BETWEEN	77,116	0	0.13	-0.42	1.4
INCOME WITHIN	77,116	-0.24	0.75	-5.93	3.4
NO GAS	77,116	0.12	0.32	0	1
AVERAGE AGE	77,116	43.54	20.87	5.25	99
CHILDREN	77,116	0.57	0.96	0	9
OWNED	77,116	0.73	0.45	0	1
DETACHED	77,116	0.22	0.42	0	1
SDETACHED	77,116	0.33	0.47	0	1
END-TERRACED	77,116	0.08	0.27	0	1
TERRACED	77,116	0.2	0.4	0	1
FLAT	77,116	0.17	0.37	0	1
* Energy, electricity and gas spending and INCOME in GBP per year. Monetary values are in real terms 2005 prices. Gas prices are in GBP per 10^7 kilocalories GCV. Electricity prices are in GBP per kWh.					

Table 1: Summary statistics of variables

The household energy spending levels depend, among other factors, on energy price movements. In order to capture the effect of price developments we match the BHPS with annual data on average yearly UK energy prices for gas and electricity. The data is drawn from the IEA (2005) and IEA (2007).[16] The development of gas and electricity prices has been fairly similar as the UK electricity prices have largely followed those of natural gas reflecting the rapid increase in the share of electricity generated from gas and its role as the market price setter in the post liberalisation period (Newbery, 2005).

[16] The IEA data is published by the Department of Energy and Climate Change (DECC).

5. RESULTS

In order to derive the Engel curves for energy spending as well as for electricity and natural gas spending, we estimate several specifications of Equation (8). The sample size is the same for the energy spending models (Model 1, restricted Model 1) and the electricity spending (Model 2) but it is smaller for gas spending (Model 3), reflecting the fact that more than 1,000 households in the sample do not have access to gas. In all specifications we use the FE estimator to control for cross-sectional (i.e. household) heterogeneity. For all specifications of the dependent variable we reject the null hypothesis of no heteroskedasticity at the 5% level of significance using a modified Wald test for groupwise heteroskedasticity. Since the random effects specification of each model is strongly rejected by the Hausman test and the Sargan-Hansen test (rejected at the 5% level of significance, see Table 2), we do not report the coefficients estimated by the random effects model.[17] The results are presented in Table 2.

Table 2 Regression results. FE parameter estimates.

	Model 1		Model 1 restricted		Model 2		Model 3	
Dep. Variable:	Energy Spending		Energy Spending		Electricity Spending		Gas Spending	
Variables	Coef.	t	Coef.	t	Coef.	t	Coef.	t
INCOME	1.187	4.01	1.103	3.78	0.996	3.04	0.810	1.88
INCOME SQ	-0.245	-4.00	-0.241	-3.93	-0.204	-2.97	-0.169	-1.88
INCOME TR	0.0138	4.32	0.0136	4.24	0.0121	3.38	0.00997	2.13
GAS PRICE	0.283	5.55	0.318	-13.92			0.541	38.59
ELECTRICITY PRICE	0.368	6.05	0.334	11.36	0.707	52.01		
INCOME BETWEEN	-0.225	-4.18			-0.252	-5.64	-0.127	-2.25
INCOME WITHIN	-0.0656	-1.47			-0.105	-4.53	-0.0599	-1.96
NO GAS	-0.174	-18.42	-0.173	-18.35	0.299	28.31		
AVERAGE AGE	-0.140	-9.01	-0.140	-9.16	-0.177	-10.27	-0.0803	-3.88
CHILDREN	0.0916	11.67	0.0915	11.72	0.0792	9.02	0.115	10.97
OWNED	0.0826	9.25	0.0827	9.25	0.0722	7.21	0.0740	5.89
DETACHED HOUSE	0.254	23.16	0.256	23.36	0.115	9.40	0.310	19.97
SEMI-DET. HOUSE	0.141	14.89	0.142	15.08	0.0408	3.85	0.227	16.93
END-TER. HOUSE	0.120	11.24	0.122	11.36	0.0335	2.79	0.214	14.16
TER. HOUSE	0.0886	9.17	0.0899	9.30	0.00996	0.92	0.167	12.25
Constant	1.891	2.01	2.334	2.49	4.195	3.97	-0.209	-0.15
Observations	77,116		77,116		77,116		67,941	
Number of groups	13,573		13,573		13,573		12,149	
R-squared	0.1723		0.1682		0.1481		0.0913	
Hausman test	821.6***		941.5***		841.4***		427.2***	
Sargan-Hansen test	705.5***		650.6***		584.2***		391.1***	

Notes: *** p<0.01, ** p<0.05, * p<0.1

For all models, most of the estimated coefficients are statistically significant and take the expected sign. In particular, the second and third-order coefficients of INCOME are statistically different from zero, suggesting the existence of non-linear Engel curves. The fuel price coefficients, i.e. GAS and ELECTRICITY PRICE, are positive indicating that energy spending as a whole and both electricity and natural gas spending are increasing in fuel prices.

[17] These will be made available upon request to the authors.

The three variables intended to capture measurement errors in individual energy prices, i.e. the within region differences in income (INCOME WITHIN), the gap between the average income in household's region and country income (INCOME BETWEEN), and the dummy variable to capture differences in prices due to lack of gas connection (NO GAS) are also statistically significant. This suggests that our modelling strategy to address the lack of individual energy prices is justified. An alternative approach to address the absence of individual household energy prices is to use the available regional price data as proxy for individual prices. This data is only available for the 1998-2007 period. For comparison, we show in Table A of the Appendix the regression results when we include regional prices in our model instead of the within and between differences in income as proxy for differences in individual energy prices. The results (see first model in Table A) were not reasonable as income coefficients are no longer significant. We hypothesize that this is due to the shorter time period and run our previous model (see second model in Table A) for this shorter period. Again, coefficients of income variables were not significant indicating that shortening our dataset reduces the within variation of income variables, so that it produces coefficients for the income variables that cannot be justified from an economic point of view. Thus keeping a longer time dimension and hence larger dataset is important and in this context, our approach seems to perform better than including regional prices in our model as proxies for differences in individual household energy prices.[18]

In addition, the results for the variables that are used to control for household and home characteristics are rather robust in the estimated models. The coefficient for the average household age (AVERAGE AGE) is generally negative and significant. We use the number of children (CHILDREN) as an indicator of household size. The number of children has a positive and significant impact on total energy as well as on electricity or gas spending. The variable for the ownership of homes (OWNED) is positively linked to the spending levels for the different fuels. As we do not control for durable appliances it is possible that owners tend to live longer in their homes and own and use more electricity appliances and, therefore, have higher electricity expenditures. The next group of coefficients compares how fuel spending differs for households living in different types of homes. As expected, energy spending is highest for households living in detached houses and lowest for those living in flats.[19]

In the following we discuss the coefficients and their magnitudes for the different models and then focus on the role of income and the Engel spending curves for the different fuels.

Both Model 1 and restricted Model 1 refer to energy spending. The fixed effects analyses of overall energy expenditures cover nearly 14,000 households in the sample, which includes more than 77,000 observations for the period of study. As mentioned, the only difference

[18] Differences in estimation results for the whole sample and the restricted sample might be explained by the fact that the first part of our sample period coincides with a period where GDP was evolving strongly from negative to positive (and increasing) rates of growth. This issue will be addressed in future research.

[19] Meier and Rehdanz (2008) estimate the effect of building types on household heating expenditures per room. They find that households living in flats have the lowest heating expenditures per room and the expenditures are highest for household living in detached houses.

between the two models is in the implementation of the measurement errors of the individual prices. As can be seen from Table 2, the explanatory power of the energy spending model increases when INCOME BETWEEN and INCOME WITHIN are included as explanatory variables since the R-squared value increases.

The modelled errors in the price variables using the within and between regional price differences consistently show negative coefficients. The coefficients are, in absolute terms, higher for INCOME BETWEEN, ranging from -0.252 (Model 2) to -0.396 (Model 3). For the INCOME WITHIN variable, coefficients range from -0.0599 (Model 3) to -0.105 (Model 2). It is noteworthy, that the effects are lowest for gas spending and highest for electricity spending. The estimated coefficients are significant for all models. The F-test statistics for the joint significance of the two variables range from 2.65 (Model 3) to 16.3 (Model 2) and the results are highly significant.

First, using income differences as a proxy for within and between regional price differences improves the explanatory power of the model. The estimated coefficients support our hypothesis, as described in Section 3: the higher the regional income in comparison to overall UK average income the lower the spending levels of individual households will be as they benefit from more competition and thus lower fuel prices. At the same time, a household living on an income higher than the regional average tends to have lower energy spending. As gas is the main heating fuel, and electricity is used for multiple purposes, this can explain the difference in magnitudes of the two variables. Households might want to reach a certain level of warmth in their homes, and thus they are more likely to save money on their electricity (and use their appliances to lower extents) rather than on their gas usage.

The coefficients for gas and electricity prices are positive but smaller than unity in all four models. This signifies that an increase in prices leads to an increase in spending though less than proportionate. Households reduce their energy consumption but their overall energy spending is higher.[20] The effect is similar for prices in the restricted and unrestricted Models (1). However, an electricity price increase leads to a stronger reduction in energy consumption than a gas price increase partly due to higher relative cost of using electricity for space heating. A one per cent increase in the electricity price results in approximately 0.7% increase in spending on electricity. Similarly, a one per cent increase in the gas price leads to more than 0.5% increase in spending on gas.

The interpretation of the NO GAS coefficient seems less obvious. It takes values of -0.17 for energy spending and 0.299 for electricity spending. Energy spending tends to be lower for households who use only electricity or oil. Households that do not have access to gas, tend to

[20] As we analyse electricity spending rather than electricity consumption, we can only hypothesize about the quantity adjustments. A price increase affects the budget constraint and households may simply reduce the consumed quantities of electricity and gas at the same time. Baker et al. (1898) find a large (negative) own price elasticity for electricity consumption. The cross price elasticity (gas) is positive. If electricity price increases while gas price is unchanged, households switch to gas and consume less electricity. Own price elasticity of gas consumption is smaller (negative), and the cross price elasticity is negative as well indicating some degree of complementarity in consumption of electricity and gas.

consume less energy. If households can use oil instead of gas, they may use less oil than they would use gas, as oil is relatively more expensive (IEA, 2007). The impact of NO Gas on electricity spending can be seen from Model (2). The positive coefficient for electricity shows that households without access to gas will spend more on electricity, independent of whether or not they also use oil or solid fuels. This is in line with evidence reported by Ofgem (2008). We argue that, due to absence of inter-fuel competition, these households face higher electricity prices. At the same time, it may be the case that households consume more electricity because they also use some electricity for heating. The answer is likely to be a combination of both higher electricity price and higher levels of consumption.

The AVERAGE AGE variable has negative coefficients in all models and, in absolute terms, its impact is comparatively the lowest on gas spending. Other studies have shown that age has a strong impact on energy spending. Meier and Rehdanz (2010) have, for example, shown an inverted U-shaped relation between heating expenditures per room and the average age of occupants indicating that older people tend to have difficulty in warming their homes adequately. The impact of the number of children is strongest in the case of gas spending. The comparatively high coefficient for gas spending shows that having children drives the usage of heating to a larger extent than electricity and overall energy spending.

The variable for the ownership of homes, OWNED, is positively linked to total spending on energy as well as to gas and electricity. Coefficients are highest for overall energy spending (0.083) and lowest for electricity spending (0.072). Also, Meier and Rehdanz (2010) have shown that heating expenditures are highest for owners. They argue that only a small proportion of households rent accommodation, and renters mainly live in flats while owners tend to live in other building types. Flats generally have lower heat loss-levels than, for example, detached houses.[21] This is in line with our findings with respect to building types. Spending on energy, electricity, and gas is highest for households living in detached houses and lowest for those living in flats. The difference between the impacts of building types is highest for gas spending. Here, the coefficient for DETACHED HOUSE is highest (0.31) while it is lowest for electricity spending (0.115). Again, the main driver of the difference in coefficients is the usage of the fuels. Gas bills, which mainly include spending on heating, depend to a larger extent on building type (and size), and detached houses have higher heat loss levels. Differences in the effect of building types on electricity usage might be linked to the size of homes as well as the number of residents. More space means that more electric appliances may be used.

Finally, we explore the third order function of income, i.e. the Engel spending curves for energy, electricity and gas. Looking at the first two models, ENGEL curves appear quite similar. Only the coefficient for the first order INCOME is higher in Model (1). A comparison of the coefficients of the three income variables shows a positive coefficient for INCOME, a negative coefficient for INCOME SQ and a positive coefficient for INCOME TR. This means that our ENGEL curves are S-shaped and spending for energy does not continuously increase in income

[21] Meier and Rehdanz (2008) estimate the impact of building types on household heating expenditures per room. They find that households living in flats have the lowest heating expenditures per room and the expenditures are highest if a household lives in a detached house.

at the same rate. This result is persistent for all four models, i.e. for energy, electricity as well as gas spending. However, the coefficients differ in magnitude. The Engel curve for gas spending starts at the lowest level of income and is located below the energy and the electricity spending curves. As gas is predominantly used for heating, households may try to keep a certain level of warmth and, therefore, income changes do not affect gas spending strongly. Households may, however, reduce spending on other goods rather than cutting on heating. On the other hand, an increase in income can encourage households to acquire more appliances which in turn leads to a stronger response to income changes in electricity and thus overall energy spending. Figure 2 illustrates the Engel spending curves based on the results of estimations for Models (1), (2) and (3), as given in Equation (3).

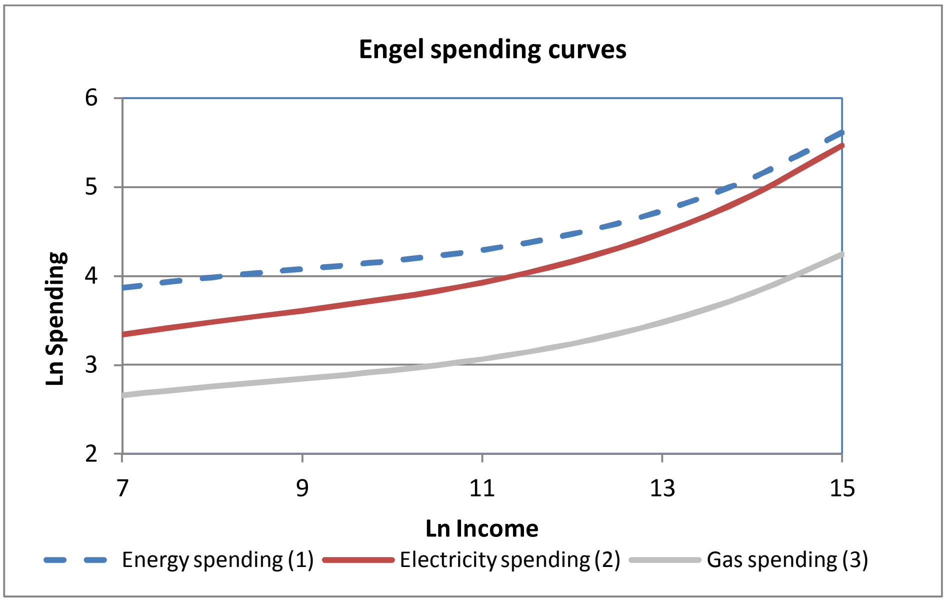

Figure 2: Engel spending curves for energy, electricity and gas[22]

The income-spending curves show how energy, electricity, and gas spending increase in income. For our range of income, no local minimum or maximum can be identified. In order to better understand these curves, we examine the first derivatives of the functions of household income as in Equation (13). The first derivative shows how energy spending changes with income and thus represents a function of income elasticity for energy, electricity, or gas spending:

$$\frac{\partial \ln f(Y_{it})}{\partial \ln Y_{it}} = \alpha_1 + \alpha_2 \ln Y_{it} + \alpha_3 (\ln Y_{it})^2 \qquad (13)$$

The income elasticities for all fuels, together or separately (Figure 3) do not exceed unity, indicating that an increase in income (at any level) leads to a less than proportionate increase in energy spending. Inflection points of the fuel spending curves and thus local minima of the

[22] Here we draw energy spending over income ranging from more than 1,000 (ln 7) to more than 3,000,000 (ln 15).

elasticity functions vary for energy, electricity, and gas spending.[23] Nevertheless, all of them occur at low income levels: the gas spending curve turns at an income level of roughly GBP 4,800, while the electricity and overall energy spending curves turn at approximately GBP 4,600 and GBP 7,200 respectively.[24] Beyond these income levels a further increase in income is spent on fuels at an increasing rate. The increase in elasticity can also be interpreted as that, at higher levels of income, energy and in particular electricity gradually begin to gain the attributes of luxury goods.[25]

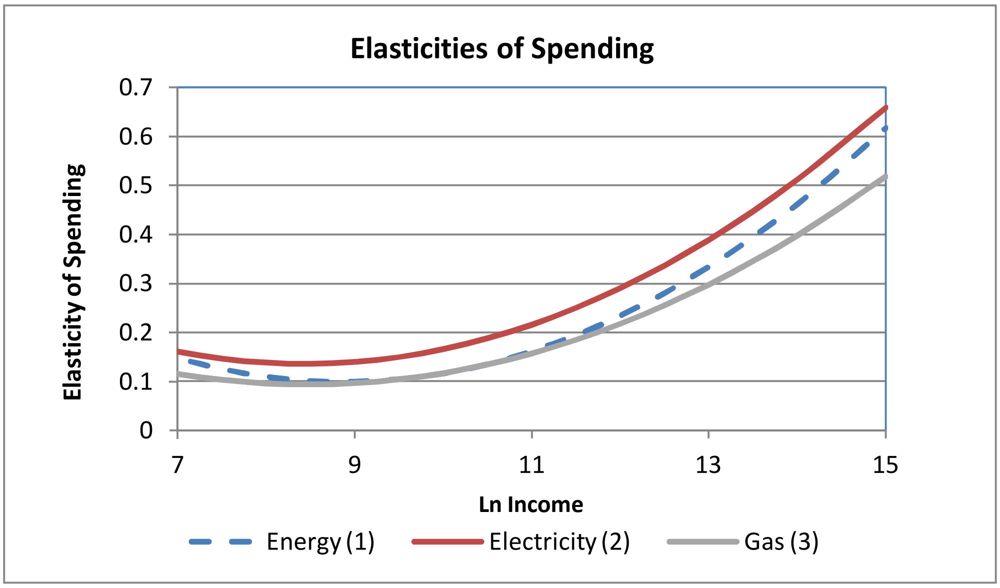

Figure 3: Income elasticities of energy, electricity and gas spending[26]

[23] The local minimum can be obtained from (13) after taking the log-derivative and solving for the income level, i.e. $y = \exp(-\alpha_2/2\alpha_3)$.

[24] In our sample, we have 2,446 households with an income below GBP 4,600 and nearly 8,000 observations with an income below GBP 7,200.

[25] Based on our model estimation, we calculate an income elasticity of spending on the different fuels at the sample mean (GBP 26,293≈ln(10)) for gas and overall energy spending equal to 0.12% and for electricity equal to 0.17%.

[26] The income elasticity of the energy spending curves is depicted in Figure (3). As shown in the graph, all elasticities first decrease and then increase in income. First, this shows, that the second derivative of the third order function of income has an inflection point. This inflection point is also at the local minimum of the income elasticity function. Accordingly, starting from very low levels of income, an increase in income leads to an increase in spending on different fuels although this will take place at a decreasing rate. Also, see Pudney (2008) for discussion of some issues related to the use of survey and income data.

THE UNIT EFFECTS AND LONG RUN

So far we have focused on households' energy spending adjustment processes in the short run. These processes might change in the long run since households might buy new appliances or undertake measures to improve the energy efficiency of homes impacting on their energy spending. In order to gain insights about the long run effects, we explore the cross-section set of unit effects that allow us to approximate the long run relationship between energy spending and income (Kennedy, 2003).

$$E_{it} = X_{it}\beta + Z_i\gamma + \alpha_i + \varepsilon_{it} \tag{14}$$

where E_{it} is energy spending in logs, X_{it} is a $K \times 1$ vector of time-varying explanatory variables, Z_i is a $P \times 1$ vector of time-invariant explanatory variables, ε_{it} is the idiosyncratic error term, and α_i captures the effect of unobserved time-invariant individual characteristics. From the first stage FE regression we can get the estimated unit effects as follows:

$$\hat{\alpha}_i = P_D(E - Xb_{FE}) = \bar{y}_i - \bar{X}_i b_{FE} \tag{15}$$

where b_{FE} is the fixed effects estimate and the projection matrix P_D allows us to get a vector of group means. In the second stage, the estimated unit effects (of the FE models) are regressed on the group means of the explanatory, time-varying variables (and also on the observed time-invariant variables, but we omit this for notational ease):

$$\hat{\alpha}_i = \alpha + \bar{X}_i\rho + \omega_i \qquad , \qquad \omega_i \sim N(0, \sigma_\omega^2) \tag{16}$$

where ρ are parameters estimated using OLS. Thus, the unit effects are decomposed into a part explained by the available between-unit information contained in X, and an unexplained part that corresponds to the residual from this second stage regression. Note that, following Kennedy (2003), this model uses only one cross-section, so OLS would produce an estimate of the long-run relationship between energy consumption and income if the relationship between unit effects and the vector of group means is not spurious but is caused by economic performance. In order to be more precise, using (14) and (16) we write the long-run elasticity of energy spending with respect to income as follows:

$$\frac{dy_{it}}{dX_{it}} = \beta + \frac{d\hat{\alpha}_i}{dX_{it}} = \beta + \frac{d\hat{\alpha}_i}{d\bar{X}_i} \cdot \frac{d\bar{X}_i}{dX_{it}} = \beta + \rho \cdot \frac{d\bar{X}_i}{dX_{it}} \tag{17}$$

where we assume that the log of income is measured by X. If short-run changes in income are "permanent", then $d\bar{X}_i/dX_{it} = 1$, and the long-run elasticity is equal to $\beta + \rho$. However, we expect that only a small part of the short-run changes in income is permanent, and hence the above derivative must be less than unity. An estimate of this derivative can be obtained if we first use the Hadrick-Prescott filter to smooth X, and then regress the "smoothed" variable against the original one. Despite its simplicity, this empirical strategy allows us to shed some light on households' long run adjustment processes.[27]

Table 3 shows the estimated coefficients of a complementary regression using the "smoothed" income variable as dependent variable. The slope of this equation is the derivative of the "smoothed" income variable with respect to the original income. As shown in Table 3, the estimated derivative is about 0.41 using OLS. This also seems to be reasonable (it is less than 1, as expected).

OLS

	Coef.	std.err.	t-ratio
INCOME	*0.413*	0.0034	120.03
Constant	5.708	0.0337	169.08
R-squared	0.4681		
obs	16371		
dep.var.	Smoothed log income (using the Hadrick-Prescott filter)		

Table 3: Parameter estimates of the permanent income equation

The regression results for the estimated unit effects (equation 16) using only logs of income as regressors are shown in Table 4. Using the estimated coefficient of Table 3 and 4, we also show the long and short run elasticities evaluated at the sample mean. The coefficients of the group means of the third order function of income show similar signs and magnitudes as for the short run fixed effects estimations. The computed short run elasticities for the group sample mean are all positive and less than one. The same applies for the long-run elasticities which are at the same time larger than their short run estimates.

The approximated long-run behavior suggests that households' change in energy spending due to changes in income is, on average larger than in the short run. That is in the long run, an increase in income leads to a stronger increase in energy spending than in the short-run. The long-run elasticity is strongest for electricity spending which is in line with the assumption that, over time, households use more electricity consuming appliances. But since gas spending increases strongest over time, it also implies households heat their existing homes to a larger extent, or even move to larger homes that require more gas spending to achieve a certain level of warmth.

[27] It should be noted that our strategy to estimate long-run elasticities relies on previous estimates of the unit effects using equation (15). These estimates are consistent provided that $T \rightarrow \infty$. When T is not large enough, $\hat{\alpha}_i$ is inconsistent because the individual averages $\bar{y}_i$ and $\bar{X}_i$ do not converge if the number of individuals increases (see Verbeek, 2008, p. 361). Therefore, in order to estimate long-run elasticities, it is important to use the maximum number of years. If instead of using our price modelling approach, we use the regional price data that is available for fewer years, the analysis no longer produces meaningful results.

	Model I		Model II		Model III		Model IV	
	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio
MLINCOME*	6.259	20.08	6.216	19.84	5.099	15.12	6.125	13.41
MLINCOME SQ*	-1.296	-20.05	-1.283	-19.75	-1.007	-14.39	-1.300	-13.73
MLINCOME TR*	0.067	20.14	0.066	19.76	0.050	13.78	0.069	14.09
Constant	-20.239	-20.24	-20.154	-20.05	-17.264	-15.95	-19.257	-13.13
R-squared	0.019		0.017		0.012		0.008	
Observations	77,116		77,116		77,116		67,941	
RHO	0.063		0.039		0.020		0.040	
Short-run elasticity	0.127		0.061		0.174		0.127	
dX_i/dX_it	0.413		0.413		0.413		0.413	
Long-run elasticity	0.153		0.077		0.182		0.143	
LR/SR ratio	1.205		1.269		1.047		1.129	

*Group means of third order function of income variables.

Table 4: Second stage estimation of unit effects[28]

6. CONCLUSIONS

This study explored the link between household energy spending and income while also analyzing other drivers of energy spending such as socio-economic determinants or building characteristics. We also examined the differences in spending on total energy, electricity and gas.

Our findings show that total spending on energy as well as on electricity and gas increase in income. The increase in spending initially slows down until it reaches a minimum at annual household income levels below GBP 8,000. Beyond this income level spending on energy as well as on electricity and gas rises at an increasing rate. The estimated Engel spending curves are slightly S-shaped.

The identified inflection points of energy spending-income curves occur at rather low levels of incomes. Households on incomes below such levels will use additional income initially to cover spending on other necessities such as food or clothing. However, using this income level as threshold where basic needs are met can be arbitrary. These households may simply only have choices between spending on food or heating and lighting.

Returning to Engel's statement about the welfare being dependent on the extent to which the needs of citizens can be met and thus costs of living can be covered and recalling Bradshaw's analysis of income and spending thresholds where basic needs are met, we come to the following conclusions. As household spending on fuels increases in income, the needs of households increase in income as well. Thus, the effort of covering costs of living becomes

[28] In this estimation we use the whole set of observations (77,116). This approach allows us to give more weight to those households with more annual observations and thus we use a weighted-type OLS estimator.

more complex the higher the income. Looking at spending on gas and linking this to spending on heating, we have shown that the link between income and gas spending is not as strong. Although gas spending also increases at an increasing rate in income the impact is not as strong as for electricity.

The shapes of the Engel spending and the elasticity of spending curves reflect the changing nature of consumption of energy, electricity, and gas as income changes. At very low levels of income households prioritize within their budget allocation between energy and other necessities. First, an increase in income is used to a larger extent to pay for food, health services, and homes. The quality and the quantity of these goods consumed probably changes first. Even though some of the additional income is spent on energy (the income elasticity is always larger than zero), it is only if income continues to increase that energy spending will, at some stage, increase at an increasing rate.

Energy is used for different types of consumption and as income changes the composition of the consumption changes. Some energy consumption is used for necessities such as heating and lighting, while some is used for normal goods, such as the usage of electrical appliances. But as income increases, the share of energy dedicated to luxury goods tends to increase and thus income elasticity of spending becomes larger at an increasing rate. Leisure activities and energy intense appliances will account for a larger share of the energy consumption mix. A rather general approximation of long run adjustment processes in energy spending shows that in the long run household energy spending increases to a larger extent in rising income than in the short-run.

Given the results and discussion in this study, we cannot recommend the use of budget thresholds or the definition of income levels where households seem to meet their basic needs. The change in household energy consumption is an individual process depending on a range of factors. Fixing energy consumption at an optimal level can only be arbitrary and will not fully satisfy the needs of consumers. We therefore suggest the exploration of transfer payments that allow households to find their own individual utility maximizing level of warmth and appliance usage. This would probably be a more efficient policy measure to overcome the increasing energy divide among households. Policies targeting residential energy use, climate change, energy efficiency of homes, energy affordability, and fuel poverty need to take income and other differences among households into consideration as consumer response to changes in income and energy prices will differ according to their initial level of income.

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APPENDIX

	New Specification		Old Specification	
Dep. Variable:	Energy Spending		Energy Spending	
Variables	Coef.	t	Coef.	t
INCOME	0.440	1.23	0.719	1.95
INCOME SQ	-0.099	-1.34	-0.109	-1.47
INCOME TR	0.006	1.45	0.006	1.58
GAS PRICE Region	0.527	8.72		
EL PRICE Region	0.156	2.03		
GAS Price (Annual)			-0.068	-0.48
ELECTRICITY Price (Annual)			0.858	4.72
INCOME BETWEEN	0.133	1.8	-0.183	-1.72
INCOME WITHIN	0.042	0.78	-0.193	-1.98
NO GAS	-0.170	-15.11	-0.170	-15.12
AVERAGE AGE	-0.090	-4.24	-0.102	-4.81
CHILDREN	0.112	10.26	0.109	9.99
OWNED	0.100	8.6	0.099	8.55
DETACHED HOUSE	0.257	17.39	0.256	17.34
SEMI-DET. HOUSE	0.143	11.47	0.143	11.47
END-TER. HOUSE	0.120	8.7	0.120	8.68
TER. HOUSE	0.100	7.87	0.099	7.86
Constant	4.559	3.53	5.306	4.49
Observations	55,509		55,509	
Number of groups	11,451		11,451	
R-squared	0.1711		0.1704	

Table A: Regressions with and without regional annual average prices (1998-2008)