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EXPLORING HOUSEHOLDS' RESPONSIVENESS TO ENERGY
PRICE CHANGES USING MICRODATA

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Exploring households' responsiveness to energy price changes using microdata

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Abstract

How households respond to energy prices is central to understanding the impact of a range of energy policies. Many empirical models and applied research rely upon outdated or generic energy price elasticities of demand, with little attention paid to whether these elasticities are the most appropriate. For example, it is typically assumed that the relevant price for the calculation of these elasticities of demand is the contemporaneous price but, except consumers on pre-payment or 'smart meters', consumers do not observe electricity prices contemporaneously. As this paper shows, what one assumes about the reference price matters empirically. Furthermore, there are good reasons to think that households of different incomes might respond differently to changing energy prices. This matters given the prominence of price as an instrument of energy policy and the need to understand distributional impacts. This paper explores these issues using a QUAIDS model and data from the UK Living Cost and Food survey. We show that different reference prices produce different elasticity estimates, and that there are important differences in how households respond to energy prices across the income distribution. These results have important implications for understanding the impact of energy prices on households and the environment.

Keywords: Distributional Analysis; Energy Elasticity; Household Energy Consumption; Microdata

JEL: Q40, Q41, D12

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1   Introduction

Households are a main focus of the UK Government's policies to tackle what is referred to as the energy 'trilemma' of security of energy supply, low carbon energy, and affordable energy. It is not hard to see why, households made up 27% of the UK's total final consumption of energy products in 2014[1], of which 87% was electricity or natural gas (hereafter, simply 'gas')[2]. In their effort to achieve low carbon energy, for instance, the UK government have brought in a Feed-in Tariff scheme (FiTS) to provide financial incentives for households to invest in renewable energy devices for their homes, this policy also aims to help with security of supply. The FiTS policy is paid for from a levy on electricity consumption, increasing the cost of electricity consumption. One would expect that this flat levy on electricity consumption will impact households across the income distribution differently but by *how much* requires the kind of detailed estimates presented in this paper. Similarly, the UK Government introduced a Carbon Price Floor in 2013, complementing the operation of the EU Emissions Trading Scheme, with the aim of supporting a higher price for carbon emissions. One effect of which was to increase the cost of electricity generation, given lags in the development of new low carbon generating capacity. The distributional impact of this increase in electricity prices on households depends on how households respond to changes in energy prices. Finally, there has been a recurring debate in the UK about measures to control energy prices though some sort of 'cap' on energy prices. All three of these policies will impact, directly and indirectly, on energy prices for UK consumers. There are a number of other examples of energy policy initiatives which will impact on energy prices, and which will therefore have differential distributional impacts which need to be understood.

Aside from these more microeconomic impacts, there are also economy-wide impacts of these interventions which rely upon microeconometric evidence. Economy wide anal-

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[1] https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/449134/ECUK_Chapter_3_-_Domestic_factsheet.pdf

[2] This was comprised of 62.7% gas and 24.5% electricity, while the other 13% comprised: 1.1% coal, 4.4% Bioenergy, 6.7% Petroleum, with <1% other solid fuels.

yses of changes in energy prices or in the efficiency of energy use typically makes use of energy-environment-economy models such as computable general equilibrium (CGE) models (examples include: Beckman et al. (2011); Böhringer and Rutherford (2013); Allan et al. (2014); Fujimori et al. (2014); Lecca et al. (2014)). These models rely on the kind of household energy elasticity measures presented in this paper, and as Hanley et al. (2009) note the results of these analysis depend heavily on such empirical concerns. More generally, these kinds of household elasticity estimates could usefully contribute to a wider range of economic analysis. For instance, in the approach of Igos et al. (2015), combining life cycle assessment, partial and general equilibrium approaches. Or in the the calibration of bioenergy models which are surveyed in Kretschmer and Peterson (2010). The number of uses for these estimates is large, and it is on these small set of numbers that much of the sensitivity of applied modeling of the energy-economy-environment interaction rests.

To help develop this literature further, this paper presents estimates of Great Britain (GB) price elasticities of demand for electricity and gas. A variant of the almost ideal demand system (AIDS) of Deaton and Muellbauer (1980) is adopted, using data from the Living Cost and Food (LCF) Survey for 2007-2014 (ONS, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014). In doing so, we explore whether there is variation in these estimates as we consider different lags of the price index and as we move across the income distribution. It is well understood that the magnitude of households' demand response to energy price changes will have important implications for their environmental impacts. In applied work it is almost always the case that we consider households response to contemporaneous price change when, in fact, households rarely observe price changes with anything like this degree of timeliness. In addition, as we consider the important overlap in the energy trilemma between measures to deliver a decarbonized energy system and to tackle fuel poverty and energy affordability, we need to develop a better understanding of differences in household behaviour across the income distribution. This paper makes an important contribution to our understanding in both these areas. The remainder of this paper

is organized as follows: Section 2 reviews the relevant literature, Section 3 introduces the model estimated here, Section 4 describes the data used in this analysis, Section 5 presents our results and Section 6 concludes.

2 Literature review

In order to motivate and explain the context for the methodology used in this paper, this section provides a brief literature review focussing on the existing empirical literature on estimating household elasticities of demand for energy from microdata. There are two main aims, firstly to discuss the main methods of estimating these parameters and secondly, to review the variation in existing estimates of these parameters.

Our starting point in thinking about estimating household elasticities of demand for energy is Micklewright (1989). This paper powerfully and memorably makes the case for estimating energy elasticities at the household level, rather than defaulting to estimating aggregate economy-wide elasticities (standard practice prior to Micklewright (1989)):

> "A study of demand for carrots could safely be presumed to be free of aggregation errors since household characteristics pertaining to carrot demand will not vary in a way that remains unexplained to any significant degree in an aggregate model. However, heterogeneity is present on a massive scale when we consider household energy demand." (Micklewright, 1989, 264)

The essential point of Micklewright (1989) is that it is important to condition on the many different characteristics of households in estimating their responsiveness to changes in energy prices. Failure to do so renders any conclusions derived from these estimates potentially unsound. Previous studies at that point had instead focused on understanding how aggregate household energy demand responded to changing energy prices. Given heterogeneity across households, there were clear reasons to believe that this approach could be improved upon. In a similar way, this paper will explore elasticity estimates across the income distribution to shed further light on differences across households.

Studies which do not exploit microdata to produce household level estimates tend instead to use aggregate level (e.g. national, regional, etc) data. One example[3] is Bernstein et al. (2006) who used a reduced–form modeling approach. Two reasons typically explain this choice of approach, firstly data availability and secondly computational/statistical considerations. In Bernstein et al. (2006) the emphasis is on producing regional level estimates which, as a result of reduced sample sizes at a regional level in survey data, can be difficult to estimate with microdata. In addition to being easier to estimate these models, using this reduced–form approach also enables the estimation of long and short run elasticities, compared to the short-run elasticities produced by the AIDS type modeling used in this paper (explained in detail in the next section) and in Micklewright (1989). However, it does so without conditioning on the characteristics of the individual residential consumers as Micklewright (1989) emphasizes is important, and Espey and Espey (2004) argues provide more accurate estimates albeit at a computational and data cost.

The results of Micklewright (1989) are in line with those of Baker et al. (1989), although the former emphasizes the impact of differences in household characteristics more intuitively, whilst the latter provides the theoretical framework under which this issue can be examined. Baker et al. (1989) is one of the most widely used and cited studies on the responsiveness of households to changes in the price of energy. Using data from the Family Expenditure Survey (the predecessor of the LCF survey used in this paper), and estimating a model based on the AIDS specification, Baker et al. (1989) produced price and income elasticity of demand estimates for electricity and gas. From a theoretical perspective, the own price elasticity estimates in Baker et al. (1989) are reasonable in terms of their sign, with increases in gas and electricity prices leading to reductions in gas and electricity prices respectively, and in their magnitude with a 1% increase in price

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[3]There are a number of similar studies, for instance Summerfield et al. (2010) and Hunt et al. (2003), which focus on estimating aggregate price elasticities for 'energy' as a whole for the aggregate economy. However, given this paper's interest in household level electricity and gas elasticities, this existence of this literature is noted and not discussed further. Similarly, we do not further discuss the interesting work of Reiss and White (2008) who explore the responsiveness of household electricity demand to sudden changes in prices.

leading to a 0.758% decrease in electricity consumption and a 0.311% decrease in gas consumption. Similarly, the income elasticity of electricity and gas demand estimates seem plausible; with estimates of 0.131 and 0.115 respectively.

One thing that stands out from the results of Baker et al. (1989), is that the cross price elasticities have different signs and magnitudes. The results suggest that an increase in the price of gas increases consumption of electricity (and therefore these goods are substitutes). A 1% increase in gas prices increases electricity consumption by 0.185%. While an increases in the price of electricity reduces gas consumption (suggesting that these goods are complements), with a 1% increase in electricity prices reducing gas consumption by 0.373%. Conditioning on the characteristics of the household, over the same time horizon, these goods must either be complements or substitutes, not both as implied by Baker et al. (1989). This situation is unsatisfactory for those engaged in empirical work requiring such estimates. Demand theory suggests that the cross price elasticities between electricity and gas should be positive (Espey and Espey, 2004, 71).

There are a small number of papers which review existing empirical estimates of household elasticities of demand starting with Espey and Espey (2004) who provide a meta-analysis of household elasticities of demand for electricity using 31 studies published between 1971 and 2000. The short and long run price elasticities had mean and median values of -0.35 and -0.85 and -0.28 and -0.81 respectively. For income elasticities, they found the short run average elasticity to be 0.28 (0.97 in the long run) and a median of 0.15 (0.92 in the long run). A more recent summary paper in this area (Cho et al., 2015) found that almost all of the estimates of residential electricity elasticities of demand in the literature have the own price elasticity of demand for electricity being negative, indicating that as the price of electricity increases, electricity consumption decreases (as we would expect). These estimates range from -2.25 (Espey and Espey, 2004) to the only positive estimate at 0.983 (Jamasb and Meier, 2010), more generally they found the own price elasticity of demand in the literature were typically between zero and one.

The Jamasb and Meier (2010) study, importantly for our purposes, was carried out

for Great Britain (i.e. the United Kingdom without Northern Ireland) as is our work here. They used a panel data approach with the British Household Panel Survey (BHPS) to estimate price and income elasticities of demand. Unlike Baker et al. (1989) who take a structural equation modelling approach, Jamasb and Meier (2010) estimate fixed and random effect models and test between these (concluding that the fixed effect approach is the most appropriate). Using panel data for this kind of study has some advantages, namely that one can control for time invariant household specific characteristics in your estimation. Interestingly, Jamasb and Meier (2010) do not include any weather variables, nor do they include regional fixed effects. Given the importance of weather fluctuations on energy use this is a key weakness of their study. In addition, one important downside to using the BHPS data for this kind of study is that it is an annual dataset, as most panel datasets are. This means that you cannot control for, or explore, the seasonal variation in energy use by households, and in energy prices, which is so important.

It is worth noting that most of the papers reviewed in Cho et al. (2015) use aggregate rather than micro data. Partly this is a reflection of the focus of their own paper, focusing on spatial spillover effects, but it also reflects the relative lack of studies using microdata given difficulties in getting these kinds of data on which to estimate such elasticities. Cho et al. (2015) also produce their own estimates of the elasticity of demand for electricity for the residential sector in South Korea. In line with Bernstein et al. (2006), they estimate a reduced form demand model rather than a structural model to understand household responses to changes in energy prices. Given that they then extend this model to capture spatial heterogeneity, this is a sensible route to proceed to explore this spatial dimension. However they do so at the cost of being unable to capture the heterogeneity of households which Micklewright (1989) emphasized as critical in understanding the true responsiveness of households to changing energy prices. Cho et al.'s (2015) estimates suggest an own price elasticity of -0.13 with a gas cross-price elasticity of demand for electricity of 0.18, although neither are statistically significant at the 5% level. Cho et al. (2015) do consider a sub-national dimension to understanding residential (as well

as manufacturing, agricultural and retail) demand for electricity, however they do not produce sub-national elasticity estimates. Rather they incorporate regional heterogeneity through the use of spatial econometric models enabling them to capture 'spillover' effects between areas.

Compared to all the studies which have sought to produce estimates of household energy price elasticities of demand, and mentioned so far, relatively little work has been done to unpick these economy-wide elasticity estimates. Furthermore, most of the literature views the production of such elasticity measures as little more than a necessary step in producing other outputs. However, there is growing recognition in the literature that this approach misses much that is important in capturing household behaviour. There is a nascent literature studying the broader area of how household energy demands evolve which has begun to bring prominence to this issue. One recent paper (Volland, 2017) considers the important and, until now, largely neglected issue of how household attitudes shape their energy demands. Volland (2017) use panel data from the British Household Panel Survey to begin to unpick the relationship between household attitudes to risk and their energy demands. It is clear that we must move away from a top down and generic understanding of how household energy demands evolve. This paper aims to contribute to this emerging literature by illustrating the important differences between households, even just on the one dimension of income, with respect to their energy demands.

3   Demand system modelling

Having briefly reviewed the estimates that already exist in the literature and the means used to produce these estimates, in this section we outline the methodology that we will use to produce our elasticity estimates using household data for GB. Given that we have cross section data which is quarterly in nature, something which is important to capture the seasonality of household energy demand, we cannot use the alternative approach to estimating household elasticities of demand with microdata utilised by Jamasb and Meier

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(2010). Therefore in this paper we will utilise a variant of the almost ideal demand system (AIDS) of Deaton and Muellbauer (1980) previously used for this purpose by Baker et al. (1989). This has been a hugely influential and widely used approach to estimating demand systems. The subsequent improvement to the model by Banks et al. (1997), incorporating non-linear Engel curves to better align with empirical evidence is known as the quadratic almost ideal demand system (QUAIDS), and this is the variant that we use in this paper. This section begins with an introduction to the AIDS model, before showing the extension embodied in the QUAIDS model to incorporate non-linearities in the Engel curves. The final part of this section provides the elasticity calculations implemented in this paper.

3.1 Almost ideal demand system

This section details the AIDS model of Deaton and Muellbauer (1980) which superseded the previous Rotterdam and translog models as the dominant approach to estimating demand systems. The first element of this model is the cost function, which is linearly homogeneous in prices, p, and is represented as:

$$\log c(u, p) = \alpha_0 + \sum_k \alpha_k \log p_k + \frac{1}{2} \sum_k \sum_j \gamma_{kj}^* \log p_k \log p_j + u \beta_0 \prod_k p_k^{\beta_k} \tag{1}$$

From which it is straightforward to derive the budget share for good i, w_i, as:

$$\frac{\partial \log c(u, p)}{\partial \log p_i} = \frac{p_i q_i}{c(u, p)} = w_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i u \beta_0 \prod p_k^{\beta_k} \tag{2}$$

where, $\gamma_{ij} = \frac{1}{2}(\gamma_{ij}^* + \gamma_{ji}^*)$. A consumer maximising her utility will set $c(u, p)$ equal to total expenditure m. This can then be used to derive a demand function for this model in expenditure shares as:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log\{m/P\} \tag{3}$$

where P is the price index.

Subject to some restrictions outlined in Deaton and Muellbauer (1980) (relating to adding up, homogeneity, and symmetry), equation (3) represents a series of demand equations, in other words a demand system encompassing all expenditure. Changes in total real expenditure impact on the system through the β_i parameter, and changes in relative prices operate through the γ_{ij} term. In moving to consider how one might aggregate such a system across households, Deaton and Muellbauer (1980) augment equation (3) to incorporate a parameter k_h which controls for a range of what one might call 'demographic' characteristics. This provides a generalised version of equation (3) as:

$$w_{ih} = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log\{m_h/k_h P\} \tag{4}$$

The importance of equation (4), lies in the fact that, as Deaton and Muellbauer (1980) show, under reasonable assumptions one can consider these aggregate expenditure shares to be the budget shares of the 'rational representative household'.

3.2   Quadratic almost ideal demand system

The essential difference between the AIDS and the QUAIDS model relates to the specification of the relationship between expenditure on goods in the system and income, commonly represented as Engel curves. If households of different income levels react (via their expenditure on certain goods) differently to a change in their income, then the AIDS formulation will not capture these effects, but the QUAIDS model will. In our dataset, we can see from Figure 1 and 2 that both electricity and natural gas have Engel Curves which exhibit non–linearities even when the data are split out by income quintile; ex–ante motivating the selection of the QUAIDS model[4]. Ex-post consideration of the model results will determine whether this is indeed appropriate.

[Figure 1 - 2 about here.]

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[4]Note: Kernel-weighted local polynomial (degree 2) smoothing.

In order to capture these non-linearities, Banks et al. (1997), extend Equation 3 to give:

$$w_i = \alpha_i + \sum_j^n \gamma_{ij} \ln p_j + \beta_i \log \left[\frac{m}{a(\mathbf{p})} \right] + \frac{\lambda_i}{b(\mathbf{p})} \left\{ \ln \left[\frac{m}{a(\mathbf{p})} \right] \right\}^2 \tag{5}$$

where $a(\mathbf{p}) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln \mathbf{p_i}$ and $b(\mathbf{p}) = \prod_{i=1}^{n} \mathbf{p_i}^{\beta_i}$ (the Cobb-Douglas price aggregator). The first two terms are the same in Equations 3 and 5, the difference is the alteration of the specification of the impact of income on expenditure shares. In Equation 3 expenditure is linear in income. In Equation 5 the linear term is still there, but there is an additional non-linear term $\frac{\lambda_i}{b(\mathbf{p})} \left\{ \ln \left[\frac{m}{a(\mathbf{p})} \right] \right\}^2$ to capture non-linearities in the impact of income on expenditure shares. Note, importantly, that this non-linear term depends explicitly on prices. This means that the Engel curves for different goods can take different forms, better reflecting observed heterogeneity.

In order to capture differences between households which, for example, are based on demographic characteristics, requires expenditure shares which depend upon these characteristics. This has been outlined by Poi (2002). The essential modification adds into equation 5 a term to scale the expenditure function. This is best explained as follows. First we define $e^R(\mathbf{p}, \mathbf{u})$ as the household expenditure function and $\mathbf{z}$ as a vector of household characteristics. We then define a new function $m_0(\mathbf{p}, \mathbf{z}, u) = \bar{m}_0(\mathbf{z}) \times \phi(\mathbf{p}, \mathbf{z}, u)$. This can then be used to produce a new expenditure function $e(\mathbf{p}, \mathbf{z}, u) = m_0(\mathbf{p}, \mathbf{z}, u) \times e^R(\mathbf{p}, u)$ which scales household expenditure according to some function of its characteristics $\mathbf{z}$. Central to this scaling are the two terms $\bar{m}_0(\mathbf{z})$ and $\phi(\mathbf{p}, \mathbf{z}, u)$, which we now define. The first, $\bar{m}_0(\mathbf{z}) = 1 + \rho'\mathbf{z}$ depends on the vector of household characteristics and some estimated parameters, basically estimating the effect of these characteristics on household expenditure. The second, $\phi(\mathbf{p}, \mathbf{z}, u)$, captures changes in relative prices and differences in the composition of expenditure across different types of goods by households. In practice this is parametrised as:

$$\ln \phi(\mathbf{p}, \mathbf{z}, u) = \frac{\prod_{j=1}^{k} p_j^{\beta_j} (\prod_{j=1}^{k} p_j^{\eta_j' \mathbf{z}}) - 1}{\frac{1}{u} - \sum_{j=1}^{k} \lambda_j \ln p_j} \tag{6}$$

This enables the introduction of this scaling by the demographic characteristics into the expenditure share equation (Equation 5 above) as follows:

$$w_i = \alpha_i + \sum_{j}^{n} \gamma_{ij} \ln p_j + (\beta_i + \eta_{\mathbf{i}}' \mathbf{z}) \log \left[\frac{m}{\bar{m}_0(\mathbf{z}) a(\mathbf{p})} \right] + \frac{\lambda_i}{b(\mathbf{p}) \mathbf{c}(\mathbf{p}, \mathbf{z})} \left\{ \ln \left[\frac{m}{\bar{m}_0(\mathbf{z}) a(\mathbf{p})} \right] \right\}^2 \tag{7}$$

where $c(\mathbf{p}, \mathbf{z}) = \prod_{j}^{n} p_j^{\eta_{\mathbf{j}}' \mathbf{z}}$.

Equation 7 makes clear how this scaling by household characteristics is implemented into the demand system affecting both the linear and quadratic expenditure terms. This provides us with a model which allows for differences in the shape of the Engel curves for different goods, and allows us to control for the characteristics of each household in estimating their responsiveness to changes in prices. This QUAIDS model is the model which we will implement later in this paper. Having outlined the AIDS and QUAIDS model, the final element to review is how one calculates the elasticities in such a model. The next section outlines the calculation of the compensated (Hicksian) and uncompensated (Marshallian) price elasticities of demand, and the income (expenditure) elasticity of demand.

3.3   Price elasticities

Having estimated this model the main task is to calculate price and income elasticities of demand. This section details how this is done for both the compensated and uncompensated elasticities of demand. Hicksian (compensated) elasticities of demand differ from Marshallian (uncompensated) elasticities of demand in that the former keep the consumers' utility constant while the latter keeps her income constant. The term compensated refers to the assumption that we make in the Hicksian case that the consumer

receives a compensation in their income in response to the price change to maintain the initial utility level. In practice what this means is that the compensated elasticity reflects only the substitution effect, unlike the uncompensated elasticity of demand which also includes an income effect.

The uncompensated price elasticity of demand for the QUAIDS model is:

$$
\epsilon_{ij} = -\delta_{ij} + \frac{1}{w_i} \left(\gamma_{ij} - \left\{ \beta_i + \boldsymbol{\eta_i'z} + \frac{2\lambda_i}{b(\boldsymbol{p})c(\boldsymbol{p},\boldsymbol{z})} ln \left[\frac{m}{\bar{m}_0(\boldsymbol{z})a(\boldsymbol{p})} \right] \right\} \mathrm{x} \right.
$$
$$
\left. \left(\alpha_j + \sum_l \gamma_{jl} ln p_l \right) - \frac{(\beta_j + \boldsymbol{\eta_j'z})\lambda_i}{b(\boldsymbol{p})c(\boldsymbol{p},\boldsymbol{z})} \left\{ ln \left[\frac{m}{\bar{m}_0(\boldsymbol{z})a(\boldsymbol{p})} \right] \right\}^2 \right) \quad (8)
$$

While the compensated price elasticities of demand are obtained through application of the Slutsky equation:

$$
\epsilon_{ij}^C = \epsilon_{ij} + \mu_i w_j \quad (9)
$$

The income (expenditure) elasticities of demand are calculated as:

$$
\mu_i = 1 + \frac{1}{w_i} \left\{ \beta_i + \boldsymbol{\eta_i'z} + \frac{2\lambda_i}{b(\boldsymbol{p})c(\boldsymbol{p},\boldsymbol{z})} ln \left[\frac{m}{\bar{m}_0(\boldsymbol{z})a(\boldsymbol{p})} \right] \right\} \quad (10)
$$

Having outlined the demand system, and the calculation of each of the key elasticities, the next section describes the data used in this empirical exercise.

4   Data and estimation

The data used in this paper come primarily from the Living Cost and Food Survey (previously known as Expenditure and Food Survey) produced annually by the UK Office of National Statistics. The questions in the survey cover a range of topics related to the household. These include: household income, expenditure by the household on different goods and services, and housing details. In this study we use data from this survey for

the period covering 2007-2014. We extract from the survey data information related to the energy consumption of households, household demographic characteristics, housing characteristics (including ownership of domestic appliances), and household income. A summary of the variables extracted from the survey is contained in Table 1.

[Table 1 about here]

In selecting household characteristics to include in the QUAIDS model our starting point was the factors controlled for in Baker et al. (1989). While a quarter of a century have passed since its publication, Baker et al. (1989) provides an useful starting point in the exploration of these same issues in this present study. In updating these control variables, we added household ownership of televisions, dishwashers and internet connection. Figure 3 demonstrates the change, and in some cases lack of change, in appliance ownership by UK Households over the 5 decades to 2014. We can see the emergence of washing machines as a household staple, the ever presence of televisions in households, and the more recent developments in tumble dryer, DVD player, dish-washer, microwave and computer ownership.

[Tables 2 - 3 about here]

In addition to those data taken from the Living Cost and Food Survey, this paper utilised information on the average temperature in each region of the UK in each of the quarters during which measurements of income and expenditure were taken. These data came from the UK Meteorological Office or 'Met Office', and enabled us to match each quarter-region data entry with the appropriate average outside air temperature. Data on gas prices, electricity prices, and the general price level were taken from the UK Department of Energy & Climate Change. Descriptive statistics for each of the variables, by year, are contained in Table 2.

[Figure 3 about here.]

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These models have traditionally been estimated by maximum likelihood, for example using commands written by Poi (2002). More recently there has been a move to use nonlinear seemingly unrelated regression to estimate these demand systems for largely computational reasons (e.g. Poi (2008, 2012))[5]. This is the approach used in this paper where we estimate the quadratic version of the AIDS model developed by Banks et al. (1997), outlined earlier. Finally, given the inclusion of a regional level covariates in these estimation (the temperature variable), cluster robust standard errors are used in all estimations. The next section presents our estimation results.

5 Results

This section is structured into two parts. First, we review the results for the whole of Great Britain, varying the price vector that is used for electricity and gas. Second, we present our estimates of the elasticity of demand for each of five income quintiles. We focus on the elasticity estimates derived from these results using the formula outlined earlier rather than discussing individual model parameter estimates, although these are available on request and were sent to the referees. The only element which we will comment directly on here is that the coefficients (λ) on the non–linear income term for all three goods (electricity, gas and non-energy) are all highly significant for all our models, justifying the selection of the QUAIDS and not the AIDS model in our analysis.

5.1 Price elasticities of demand using different price lags

We outlined earlier that it has typically been assumed in the literature that the relevant reference price when estimating elasticities of demand for electricity and gas is the contemporaneous electricity and gas price. The sensitivity of empirical results to this assumption, to our knowledge, has never been tested. There are a number of reasons to question this assumption. The first, and most obvious, is that with the exception

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[5]It is perhaps worth noting that, as Poi (2012) points out, this approach is: "equivalent to the multivariate normal maximum-likelihood estimator for this class of problems".

of customers on pre-payment meters (15% of UK electricity consumers[6]) and those just getting access to smart meters (just over 3% of UK electricity and gas consumers by the end of 2014[7]), consumers do not observe electricity prices contemporaneously. The second, is that consumers on direct debit and credit meters typically receive bills with a lag, thus the 'signal' that they receive about the cost of their electricity and/or gas use is received with some delay after the quarter in which they consume that electricity and/or gas. Finally, even if one believed that consumers track the wholesale price of electricity contemporaneously, they are not billed on the basis of these prices.

For these reasons, we begin our analysis of how households respond to changing electricity and gas prices by considering the elasticity of household electricity and gas demand with respect to different reference prices, namely: contemporaneous prices, with a one quarter lag, with a two quarter lag, with a three quarter lag, and with a four quarter lag. Table 4 presents the results from our model of the price elasticity of demand for electricity and gas using these different reference prices.

[Tables 4 & 5 about here]

Results are presented for the compensated and uncompensated elasticities of demand for completeness, but they are broadly similar and we focus in this section on the compensated elasticity of demand results. We can see that for Gas, the contemporaneous price elasticity of demand for GB households is -0.655, suggesting that a 1% increase in gas prices reduces gas consumption, on average in GB, by 0.655%. This estimate is statistically significantly different from zero with a t-statistic in excess of 9.6. If instead of using the contemporaneous price we instead look at the price lagged by one quarter, we can see that the elasticity estimate drops to 0.546, with a two quarter lag in the price we can see that the elasticity falls slightly again to -0.514, thereafter (with a three and four quarter lag) the elasticity increases with it's highest value with respect to gas prices four quarters before.

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[6] https://www.gov.uk/government/statistical-data-sets/quarterly-domestic-energy-price-stastics\#history
[7] https://www.gov.uk/government/statistics/statistical-release-and-data-smart-meters-great-britain-quarter-1-2017

For electricity, a similar pattern is observed with the contemporaneous elasticity of demand estimate (-0.357) higher than the elasticity with respect to prices in the quarter before (-0.350) and two quarters before (-0.251, albeit only statistically significantly different from zero at the 10% level) before increasing again with respect to prices three (-0.493) and four quarters before (-0.876). In terms of the cross price elasticity of demand between electricity and gas, we can see that the cross price elasticity estimates, unlike Baker et al. (1989), have a consistent sign and indicate that these goods are complements. However, only with respect to prices lagged by two quarters are these estimates statistically significantly different from zero, and then only at the 10% level.

These results show two things. Firstly, they provide useful information on how GB households' electricity and gas demands respond to electricity and gas prices. Secondly, these results suggest that the common use of contemporaneous prices in the estimation of household elasticities for electricity and gas may be over-estimating the size of the response of demand to changes in prices if the prices that consumers actually observe and respond to are the prices in the quarter or two quarters before (and underestimating the magnitude of the response if the relevant price signal is three or four quarters before). There are good reasons, outlined earlier, to believe that in the UK the relevant price signal for households is not contemporaneous. Which alternative one should use, absent a more formal test, is something that each analyst should decide upon, although we do not think it likely that households take a full year to recognise electricity/gas prices changing, and with billing typically lagged by a quarter, we would tend to use the estimates lagged by at least a quarter and more likely two quarters. In the next set of results we focus on the results from our model with the best log-likelihood which is the results using price data lagged by two quarters.

5.2 Price elasticities of demand across the income distribution

Key to understanding the distributional impacts of a range of energy policies which affect the price that consumers pay for electricity and gas is understanding how the value of

the price elasticity of demand changes across the income distribution. These results are presented in Tables 6 & 7.

[Tables 6 & 7 about here]

For natural gas, as we move from the lowest income quintile group to the highest income quintile group the elasticity of demand with respect to the price, while inelastic in all cases, becomes less so. Given that gas is used by households primarily for heating and cooking, it makes sense that the poorest households have the most inelastic demand for gas; with a 1% increase in gas price reducing gas consumption on average among this group by 0.394%. This estimate is barely insignificant at the 10% level, this means that for the poorest households we cannot conclude that their elasticity of demand for gas is anything other than perfectly inelastic (elasticity estimate of zero) based on these results. For all other income groups, gas consumption appears to respond inelastically to changes in gas prices, with households in the second income quintile on average reducing consumption of gas by 0.432% in response to a 1% increase in gas prices. This compares to the highest income households who, on average, would reduce their gas consumption by 0.698% in response to the same change in gas prices.

For electricity a similar pattern emerges of lower income households having less elastic demand than higher income households. Here we find that electricity demand for the three lowest income quintiles in GB is inelastic with respect to changes in electricity prices, and with low t-statistic scores we must accept the null hypothesis that these elasticities are not statistically significantly different from zero and thus demand is perfectly inelastic. For higher income households demand is similarly inelastic, although less so for the highest income group (-0.705) relative to the second highest income quintile (-0.450).

These results suggest that changes in energy policy which have the effect of raising electricity and gas prices will raise revenue, given that demand is inelastic, and may be attractive to government for that reason. However, what these results also demonstrate is that it will do so in a way which impacts most acutely on the poorest income households.

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Given the important role of electricity and gas in everyday life, in providing heating, cooking and use of basic household appliances, it isn't a surprise that the poorest households are less able to change their demand for energy in response to changing electricity and gas prices. It therefore remains a puzzle why much of energy policy in the U.K. focuses on measures which will increase energy prices, or will have the effect of doing so, without an associated focus on helping the poorest households who are disproportionately affected by these measures as these results illustrate.

6 Conclusions

This article has produced up-to-date estimates of household elasticity of demand for electricity and gas using microdata for Great Britain as a whole under different reference prices and across the income distribution; updating and extending Baker et al. (1989). In doing so, we have established that using contemporaneous electricity and gas prices produces higher estimates of the household price elasticity of demand than those produced using lagged prices from the quarter or two quarters before (and conversely lower estimates than those produced using prices from three or four quarters before). It is not clear, ex-ante, which of these alternative price signals is the relevant one for households in making decisions about energy consumption, however we have argued that since households generally do not observe prices contemporaneously then analysts seeking short term elasticity estimates should not use estimates produced on this basis.

Given the importance of price -directly and indirectly- in delivering UK energy policy objectives, we also explored whether there are differences in the how households respond to changes in electricity and gas prices over the income distribution. We found that for the lowest income households their gas demand responded less to changes in gas prices than higher income households, while for households in the lowest income quintile their demand for gas appears to be perfectly inelastic. For electricity, we found that for the bottom three income quintiles their elasticity of demand was statistically insignificantly different

from zero (i.e. perfectly inelastic). With the lowest income households having short-run elasticities of demand which are not statistically significantly different from zero, it is clear that increases in energy prices will disproportionately affect the households budgets of the poorest households. The results of this analysis demonstrate that the use of price as an instrument -directly and indirectly- of energy policy something which will have profound distributional impacts.
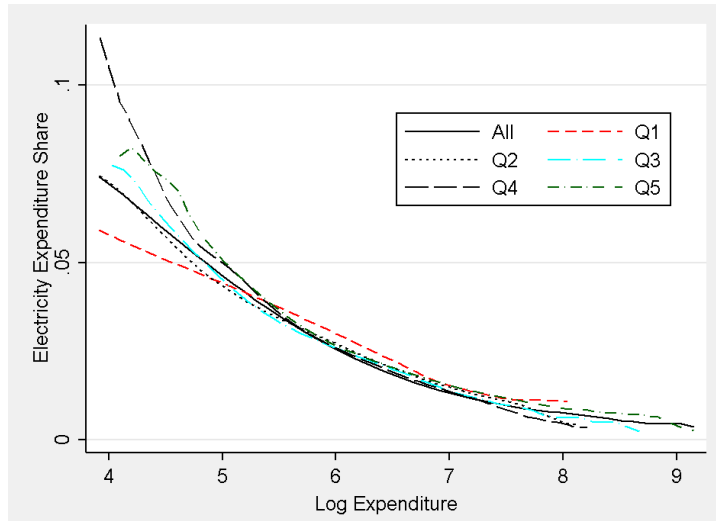
Figure 1: Engel Curve for Electricity
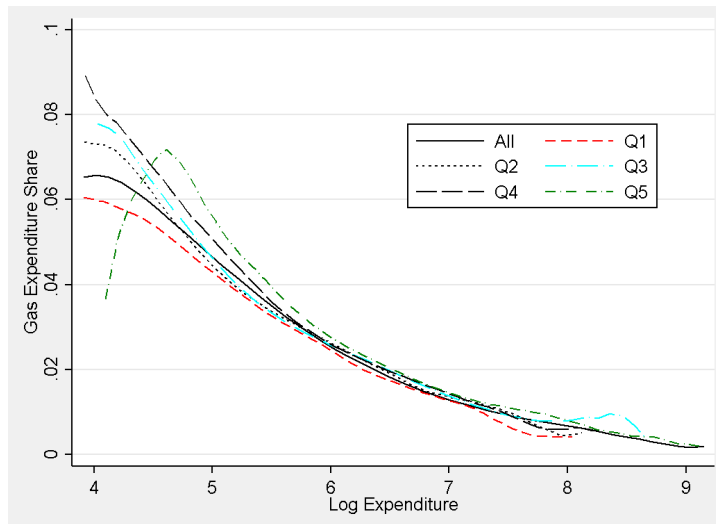
Figure 2: Engel Curve for Natural Gas
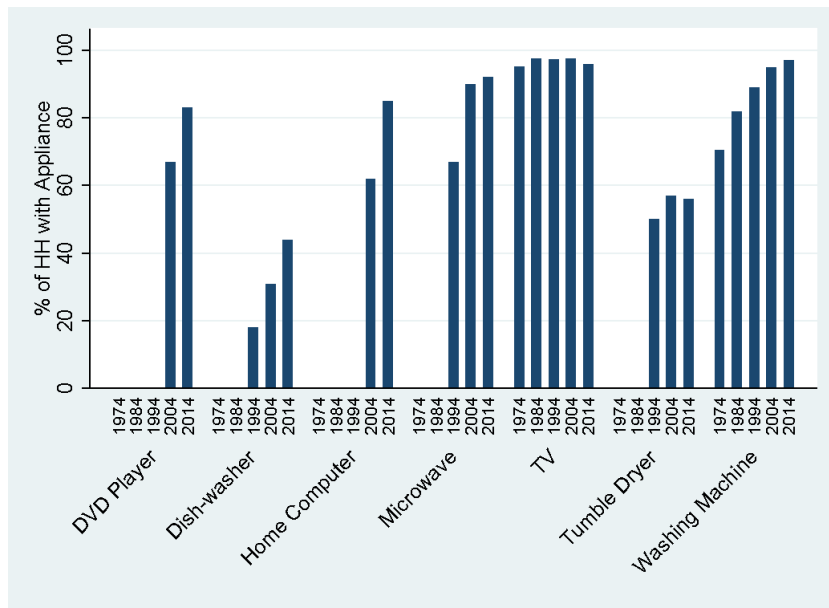
Figure 3: UK Appliance Ownership by households, 1973-2014

Variable name	Definition	Year	Source
GEXPSH	Gas expenditure/total expenditure	2007-2014	Calculated by author from Living Costs and Food Survey data
ELEXPSH	Electricity expenditure/total expenditure	2007-2014	Calculated by author from Living Costs and Food Survey data
NENER	Non-energy expenditure/total expenditure	2007-2014	Calculated by author from Living Costs and Food Survey data
EPIXY	Electricity price	2007-2014	Office for National Statistics CPIH Index 04.5.1:Electricity
GPIXY	Gas price	2007-2014	Office for National Statistics CPIH Index 04.5.2: Gas
FPIXP	Price of non-energy goods	2007-2014	Office for National Statistics CPIH Index: Excluding energy
P600	Total HH expenditure	2007-2014	Living Costs and Food Survey
log INCOME	log of normal weekly disposable household income	2007-2014	Living Costs and Food Survey
logHSIZE	log of number of people in the household	2007-2014	Living Costs and Food Survey
KIDSD	=1 if there are children under 5 years old in HH	2007-2014	Living Costs and Food Survey
HADULT	=1 if any adult in HH is out of labour force	2007-2014	Living Costs and Food Survey
AGE40	=1 if HH head is aged >40	2007-2014	Living Costs and Food Survey
AGE65	=1 if HH head is aged >65	2007-2014	Living Costs and Food Survey
logROOMS	log of number of rooms in the accommodation	2007-2014	Living Costs and Food Survey
ELECTONLY	Electricity only in the HH	2007-2014	Living Costs and Food Survey
GCH	Gas central heating in HH	2007-2014	Living Costs and Food Survey
ECH	Electric central heating in HH	2007-2014	Living Costs and Food Survey
OCH	Oil central heating in HH	2007-2014	Living Costs and Food Survey
TEMP	Average outside temperature in the region and quarter of expenditure	2007-2014	http://www.metoffice.gov.uk/climate/uk/summaries/datasets
WASH	=1 if there is a washing machine in the accommodation	2007-2014	Living Costs and Food Survey
FRIDGE	=1 if there is a fridge in the accommodation	2007-2014	Living Costs and Food Survey
TELE	=1 if there is a television in the accommodation	2007-2014	Living Costs and Food Survey
DISH	=1 if there is a dishwasher in the accommodation	2007-2014	Living Costs and Food Survey
WWW	=1 if there is internet access in the accommodation	2007-2014	Living Costs and Food Survey
COUNCIL	=1 if accommodation is rented from local authority	2007-2014	Living Costs and Food Survey
RENT	=1 if accommodation is privately rented	2007-2014	Living Costs and Food Survey
RENTFREE	=1 if accommodation is lived in rent free	2007-2014	Living Costs and Food Survey
OWNCOMP	=1 if accommodation is owned outright	2007-2014	Living Costs and Food Survey
SPRAUT	=1 if expenditure in April-June or October-December	2007-2014	Living Costs and Food Survey
SUMMER	=1 if expenditure in July-September	2007-2014	Living Costs and Food Survey
REGION2-REGION 11	Regional Fixed Effects	2007-2014	Living Costs and Food Survey

Table 1: Variable details

Variable	Whole Sample					Quintile 1					Quintile 2				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Gas Exp Share	41,429	0.031	0.034	0.000	0.250	7,871	0.042	0.049	0.000	0.250	8,655	0.036	0.037	0.000	0.250
Elec Exp Share	41,429	0.031	0.029	0.000	0.249	7,871	0.043	0.042	0.000	0.249	8,655	0.036	0.032	0.000	0.249
Non-Energy Exp Share	41,429	0.937	0.054	0.504	1.000	7,871	0.915	0.077	0.504	1.000	8,655	0.928	0.058	0.524	1.000
Gas Price	41,429	0.768	0.141	0.534	1.006	7,871	0.767	0.140	0.534	1.006	8,655	0.768	0.141	0.534	1.006
Elec Price	41,429	0.810	0.104	0.633	1.007	7,871	0.809	0.104	0.633	1.007	8,655	0.810	0.104	0.633	1.007
Non-Energy Price	41,429	0.914	0.051	0.834	1.000	7,871	0.914	0.051	0.834	1.000	8,655	0.915	0.052	0.834	1.000
Total Expenditure	41,429	412.145	325.375	50.035	9394.720	7,871	189.200	149.056	50.035	3104.525	8,655	279.827	173.221	50.295	3365.955
log(Income)	41,429	6.098	0.728	-3.219	7.397	7,871	5.011	0.533	-3.219	5.624	8,655	5.742	0.158	5.393	6.100
log(# people in HH)	41,429	0.723	0.525	0.000	2.197	7,871	0.279	0.432	0.000	2.197	8,655	0.566	0.492	0.000	2.197
Child <5 in HH	41,429	0.123	0.328	0.000	1.000	7,871	0.077	0.267	0.000	1.000	8,655	0.096	0.295	0.000	1.000
HADULT	41,429	0.065	0.247	0.000	1.000	7,871	0.114	0.318	0.000	1.000	8,655	0.066	0.248	0.000	1.000
AGE40	41,429	0.757	0.429	0.000	1.000	7,871	0.817	0.387	0.000	1.000	8,655	0.794	0.404	0.000	1.000
AGE65	41,429	0.278	0.448	0.000	1.000	7,871	0.441	0.497	0.000	1.000	8,655	0.428	0.495	0.000	1.000
log(# rooms in HH)	41,429	1.614	0.233	0.000	1.792	7,871	1.475	0.282	0.000	1.792	8,655	1.570	0.243	0.000	1.792
Only Elec in HH	41,429	0.144	0.351	0.000	1.000	7,871	0.182	0.386	0.000	1.000	8,655	0.160	0.366	0.000	1.000
Gas Central Heating	41,429	0.821	0.384	0.000	1.000	7,871	0.768	0.422	0.000	1.000	8,655	0.798	0.401	0.000	1.000
Elec Central Heating	41,429	0.069	0.253	0.000	1.000	7,871	0.119	0.324	0.000	1.000	8,655	0.091	0.288	0.000	1.000
Oil Central Heating	41,429	0.069	0.253	0.000	1.000	7,871	0.049	0.216	0.000	1.000	8,655	0.059	0.236	0.000	1.000
Regional Temperature	41,429	9.712	4.088	1.500	16.900	7,871	9.636	4.099	1.500	16.900	8,655	9.641	4.046	1.500	16.900
Washing Machine in HH	41,429	0.970	0.172	0.000	1.000	7,871	0.905	0.293	0.000	1.000	8,655	0.964	0.186	0.000	1.000
Fridge in HH	41,429	0.976	0.152	0.000	1.000	7,871	0.947	0.224	0.000	1.000	8,655	0.973	0.161	0.000	1.000
Television in HH	41,429	0.985	0.121	0.000	1.000	7,871	0.974	0.158	0.000	1.000	8,655	0.985	0.120	0.000	1.000
Dishwasher in HH	41,429	0.418	0.493	0.000	1.000	7,871	0.158	0.365	0.000	1.000	8,655	0.269	0.443	0.000	1.000
Internet in HH	41,429	0.755	0.430	0.000	1.000	7,871	0.430	0.495	0.000	1.000	8,655	0.628	0.483	0.000	1.000
Property rented from Council	41,429	0.166	0.372	0.000	1.000	7,871	0.396	0.489	0.000	1.000	8,655	0.234	0.424	0.000	1.000
Property Rented Privately	41,429	0.127	0.333	0.000	1.000	7,871	0.159	0.365	0.000	1.000	8,655	0.143	0.350	0.000	1.000
HH Lives Rent Free	41,429	0.011	0.106	0.000	1.000	7,871	0.018	0.132	0.000	1.000	8,655	0.014	0.119	0.000	1.000
Property Owned Outright	41,429	0.342	0.474	0.000	1.000	7,871	0.348	0.476	0.000	1.000	8,655	0.427	0.495	0.000	1.000
Spring/Autumn	41,429	0.500	0.500	0.000	1.000	7,871	0.494	0.500	0.000	1.000	8,655	0.504	0.500	0.000	1.000
Summer	41,429	0.254	0.435	0.000	1.000	7,871	0.256	0.437	0.000	1.000	8,655	0.247	0.432	0.000	1.000

Table 2: Descriptive Statistics 1

Variable	Quintile 3 Obs	Mean	Std. Dev.	Min	Max	Quintile 4 Obs	Mean	Std. Dev.	Min	Max	Quintile 5 Obs	Mean	Std. Dev.	Min	Max
Gas Exp Share	8,556	0.030	0.028	0.000	0.249	8,258	0.026	0.024	0.000	0.248	8,089	0.022	0.020	0.000	0.229
Elec Exp Share	8,556	0.030	0.025	0.000	0.236	8,258	0.026	0.020	0.000	0.247	8,089	0.022	0.017	0.000	0.213
Non-Energy Exp Share	8,556	0.940	0.044	0.546	1.000	8,258	0.948	0.037	0.567	1.000	8,089	0.956	0.030	0.648	1.000
Gas Price	8,556	0.769	0.141	0.534	1.006	8,258	0.767	0.141	0.534	1.006	8,089	0.769	0.141	0.534	1.006
Elec Price	8,556	0.811	0.104	0.633	1.007	8,258	0.809	0.104	0.633	1.007	8,089	0.810	0.104	0.633	1.007
Non-Energy Price	8,556	0.915	0.052	0.834	1.000	8,258	0.914	0.051	0.834	1.000	8,089	0.915	0.051	0.834	1.000
Total Expenditure	8,556	379.081	222.278	56.215	8788.750	8,258	488.795	247.325	50.595	3681.960	8,089	727.381	447.433	60.130	9394.720
log(Income)	8,556	6.163	0.125	5.896	6.458	8,258	6.534	0.122	6.279	6.838	8,089	7.024	0.199	6.666	7.397
log(# people in HH)	8,556	0.780	0.473	0.000	2.197	8,258	0.933	0.439	0.000	2.197	8,089	1.048	0.405	0.000	2.197
Child <5 in HH	8,556	0.135	0.341	0.000	1.000	8,258	0.154	0.361	0.000	1.000	8,089	0.150	0.357	0.000	1.000
HADULT	8,556	0.056	0.230	0.000	1.000	8,258	0.051	0.221	0.000	1.000	8,089	0.040	0.197	0.000	1.000
AGE40	8,556	0.733	0.443	0.000	1.000	8,258	0.697	0.459	0.000	1.000	8,089	0.744	0.436	0.000	1.000
AGE65	8,556	0.276	0.447	0.000	1.000	8,258	0.154	0.361	0.000	1.000	8,089	0.090	0.286	0.000	1.000
log(# rooms in HH)	8,556	1.628	0.210	0.000	1.792	8,258	1.671	0.180	0.693	1.792	8,089	1.725	0.147	0.000	1.792
Only Elec in HH	8,556	0.133	0.340	0.000	1.000	8,258	0.122	0.327	0.000	1.000	8,089	0.124	0.330	0.000	1.000
Gas Central Heating	8,556	0.832	0.374	0.000	1.000	8,258	0.849	0.358	0.000	1.000	8,089	0.854	0.353	0.000	1.000
Elec Central Heating	8,556	0.060	0.238	0.000	1.000	8,258	0.045	0.207	0.000	1.000	8,089	0.031	0.172	0.000	1.000
Oil Central Heating	8,556	0.068	0.251	0.000	1.000	8,258	0.073	0.260	0.000	1.000	8,089	0.094	0.292	0.000	1.000
Regional Temperature	8,556	9.662	4.100	1.500	16.900	8,258	9.712	4.095	1.500	16.900	8,089	9.917	4.097	1.500	16.900
Washing Machine in HH	8,556	0.986	0.118	0.000	1.000	8,258	0.993	0.081	0.000	1.000	8,089	0.997	0.053	0.000	1.000
Fridge in HH	8,556	0.984	0.127	0.000	1.000	8,258	0.986	0.117	0.000	1.000	8,089	0.990	0.101	0.000	1.000
Television in HH	8,556	0.986	0.118	0.000	1.000	8,258	0.989	0.106	0.000	1.000	8,089	0.991	0.095	0.000	1.000
Dishwasher in HH	8,556	0.393	0.488	0.000	1.000	8,258	0.528	0.499	0.000	1.000	8,089	0.746	0.435	0.000	1.000
Internet in HH	8,556	0.817	0.387	0.000	1.000	8,258	0.921	0.270	0.000	1.000	8,089	0.970	0.170	0.000	1.000
Property rented from Council	8,556	0.127	0.333	0.000	1.000	8,258	0.064	0.245	0.000	1.000	8,089	0.017	0.128	0.000	1.000
Property Rented Privately	8,556	0.138	0.345	0.000	1.000	8,258	0.115	0.319	0.000	1.000	8,089	0.081	0.273	0.000	1.000
HH Lives Rent Free	8,556	0.009	0.095	0.000	1.000	8,258	0.009	0.095	0.000	1.000	8,089	0.007	0.081	0.000	1.000
Property Owned Outright	8,556	0.386	0.487	0.000	1.000	8,258	0.287	0.452	0.000	1.000	8,089	0.257	0.437	0.000	1.000
Spring/Autumn	8,556	0.497	0.500	0.000	1.000	8,258	0.495	0.500	0.000	1.000	8,089	0.507	0.500	0.000	1.000
Summer	8,556	0.255	0.436	0.000	1.000	8,258	0.255	0.436	0.000	1.000	8,089	0.258	0.437	0.000	1.000

Table 3: Descriptive Statistics 2

			Gas Price					Electricity Price				
			Contemp.	1 Q lag	2 Q lag	3 Q lag	4 Q lag	Contemp.	1 Q lag	2 Q lag	3 Q lag	4 Q lag
Compensated	Coefficient	Gas Consump.	**-0.655**	**-0.546**	**-0.514**	**-0.675**	**-0.835**	-0.366	-0.061	-0.167	-0.152	-0.098
		Electricity Consump.	-0.122	-0.061	-0.167	-0.153	-0.098	**-0.357**	**-0.350**	**-0.251**	**-0.493**	**-0.876**
		Non-Energy Consump.	0.026	0.020	0.023	0.028	0.031	0.017	0.014	0.014	0.022	0.033
	Robust Standard Errors	Gas Consump.	**0.068**	**0.066**	**0.073**	**0.079**	**0.080**	0.103	0.102	0.099	0.099	0.098
		Electricity Consump.	0.103	0.101	0.099	0.103	0.098	**0.154**	**0.154**	**0.149**	**0.159**	**0.150**
		Non-Energy Consump.	0.003	0.003	0.003	0.003	0.002	0.003	0.003	0.003	0.003	0.003
	t-statistic	Gas Consump.	**-9.621**	**-8.220**	**-7.070**	**-8.509**	**-10.398**	-3.553	-0.600	-1.682	-1.475	-0.992
		Electricity Consump.	-1.187	-0.607	-1.689	-1.482	-1.000	**-2.316**	**-2.271**	**-1.681**	**-3.094**	**-5.857**
		Non-Energy Consump.	8.700	7.351	7.843	9.981	13.423	5.694	4.482	4.502	6.473	10.728
Uncompensated	Coefficient	Gas Consump.	**-0.661**	**-0.551**	**-0.520**	**-0.681**	**-0.841**	-0.127	-0.067	-0.173	-0.158	-0.103
		Electricity Consump.	-0.127	-0.067	-0.173	-0.158	-0.103	**-0.371**	**-0.356**	**-0.257**	**-0.498**	**-0.882**
		Non-Energy Consump.	-0.007	-0.013	-0.010	-0.005	-0.002	-0.017	-0.019	-0.019	-0.012	-0.001
	Robust Standard Errors	Gas Consump.	**0.068**	**0.066**	**0.073**	**0.079**	**0.080**	0.103	0.102	0.099	0.099	0.098
		Electricity Consump.	0.103	0.101	0.099	0.103	0.098	**0.154**	**0.154**	**0.149**	**0.159**	**0.150**
		Non-Energy Consump.	0.003	0.003	0.003	0.003	0.002	0.003	0.003	0.003	0.003	0.003
	t-statistic	Gas Consump.	**-9.703**	**-8.308**	**-7.152**	**-8.584**	**-10.471**	-1.235	-0.656	-1.739	-1.529	-1.049
		Electricity Consump.	-1.239	-0.660	-1.743	-1.533	-1.053	**-2.405**	**-2.306**	**-1.717**	**-3.128**	**-5.893**
		Non-Energy Consump.	-2.366	-4.618	-3.531	-1.938	-0.802	-5.747	-6.308	-6.157	-3.457	-0.172
Number of obs			41429	41429	41429	41429	41429	41429	41429	41429	41429	41429
Log-likelihood			194040.5	194063.2	194067.4	194046.6	194037.8	194040.540	194063.180	194067.370	194046.600	194037.840

Table 4: Price elasticities of demand, GB

[a] Own-price Elasticity Estimates in BOLD

		Non-Energy Consumption				
		Contemp.	1 Q lag	2 Q lag	3 Q lag	4 Q lag
Coefficient	Gas Consump.	0.777	0.607	0.681	0.828	0.933
	Electricity Consump.	0.488	0.412	0.419	0.646	0.974
	Non-Energy Consump.	**-0.042**	**-0.034**	**-0.037**	**-0.049**	**-0.064**
Robust Standard Errors	Gas Consump.	0.089	0.083	0.087	0.083	0.070
	Electricity Consump.	0.087	0.092	0.093	0.100	0.091
	Non-Energy Consump.	**0.004**	**0.004**	**0.005**	**0.005**	**0.004**
t-statistic	Gas Consump.	8.693	7.343	7.834	9.972	13.411
	Electricity Consump.	5.578	4.490	4.511	6.481	10.736
	Non-Energy Consump.	-10.045	-8.167	-7.878	-10.193	-14.885
[a] Coefficient	Gas Consump.	0.607	0.436	0.512	0.660	0.765
	Electricity Consump.	0.327	0.250	0.258	0.487	0.817
	Non-Energy Consump.	**-1.031**	**-1.023**	**-1.026**	**-1.038**	**-1.053**
Robust Standard Errors	Gas Consump.	0.090	0.084	0.089	0.085	0.072
	Electricity Consump.	0.089	0.094	0.095	0.101	0.093
	Non-Energy Consump.	**0.004**	**0.004**	**0.005**	**0.005**	**0.004**
t-statistic	Gas Consump.	6.739	5.192	5.728	7.720	10.602
	Electricity Consump.	3.663	2.664	2.714	4.811	8.791
	Non-Energy Consump.	**-239.955**	**-236.478**	**-211.315**	**-207.940**	**-235.535**
Number of obs		41429	41429	41429	41429	41429
Log-likelihood		194040.540	194063.180	194067.37	194046.6	194037.84

Table 5: Price elasticities of demand, GB

[a]Own-price Elasticity Estimates in BOLD

Table 6: Price elasticities of demand, GB

		Gas Price					Electricity Price				
		1st Q	2nd Q	3rd Q	4th Q	5th Q	1st Q	2nd Q	3rd Q	4th Q	5th Q
Compensated											
Coefficient	Gas Consump.	**-0.394**	**-0.432**	**-0.455**	**-0.583**	**-0.698**	0.193	0.014	-0.202	-0.111	-0.001
	Electricity Consump.	0.080	0.013	-0.202	-0.114	-0.004	**-0.357**	**-0.264**	**-0.075**	**-0.450**	**-0.705**
	Non-Energy Consump.	0.010	0.014	0.022	0.023	0.023	0.017	0.008	0.009	0.019	0.024
Robust Standard Errors	Gas Consump.	**0.244**	**0.173**	**0.109**	**0.097**	**0.106**	0.327	0.226	0.149	0.119	0.104
	Electricity Consump.	0.326	0.225	0.149	0.119	0.103	**0.477**	**0.359**	**0.266**	**0.239**	**0.237**
	Non-Energy Consump.	0.009	0.006	0.006	0.004	0.003	0.010	0.007	0.005	0.005	0.006
t-statistic	Gas Consump.	**-1.615**	**-2.504**	**-4.183**	**-6.040**	**-6.556**	0.590	0.061	-1.354	-0.936	-0.006
	Electricity Consump.	0.247	0.056	-1.362	-0.961	-0.043	**-0.750**	**-0.736**	**-0.280**	**-1.886**	**-2.978**
	Non-Energy Consump.	1.222	2.281	3.570	6.023	7.356	1.696	1.179	1.707	3.842	3.889
Uncompensated [a]											
Coefficient	Gas Consump.	**-0.398**	**-0.438**	**-0.461**	**-0.587**	**-0.704**	0.079	0.008	-0.208	-0.115	-0.007
	Electricity Consump.	0.079	0.008	-0.209	-0.117	-0.009	**0.191**	**-0.269**	**-0.081**	**-0.453**	**-0.710**
	Non-Energy Consump.	-0.023	-0.019	-0.011	-0.010	-0.010	-0.043	-0.025	-0.024	-0.014	-0.009
Robust Standard Errors	Gas Consump.	**0.244**	**0.173**	**0.109**	**0.097**	**0.106**	0.327	0.226	0.149	0.119	0.104
	Electricity Consump.	0.326	0.225	0.149	0.118	0.103	**0.477**	**0.359**	**0.266**	**0.239**	**0.237**
	Non-Energy Consump.	0.009	0.006	0.006	0.004	0.003	0.010	0.007	0.005	0.005	0.006
t-statistic	Gas Consump.	**-1.632**	**-2.540**	**-4.223**	**-6.040**	**-6.658**	0.243	0.034	-1.391	-0.964	-0.072
	Electricity Consump.	0.242	0.034	-1.403	-0.991	-0.091	**0.401**	**-0.750**	**-0.304**	**-1.895**	**-2.997**
	Non-Energy Consump.	-2.656	-3.097	-1.789	-2.533	-3.020	-4.330	-3.474	-4.408	-2.954	-1.556
Number of obs		7,871	8,655	8,556	8,258	8,089	7,867	8,631	8,595	8,266	8,070
Log-likelihood		30576.6	38813.6	43107.8	45079.1	47051.3	30937.8	38191.8	43161.9	44740.9	46895.1

[a] Own-price Elasticity Estimates in BOLD

		Non-Energy Consumption				
		1st Q	2nd Q	3rd Q	4th Q	5th Q
Compensated						
Coefficient	Gas Consump.	0.311	0.419	0.657	0.695	0.698
	Electricity Consump.	-0.273	0.252	0.277	0.564	0.710
	Non-Energy Consump.	**-0.001**	**-0.022**	**-0.031**	**-0.042**	**-0.047**
Robust Standard Errors	Gas Consump.	0.256	0.184	0.184	0.115	0.095
	Electricity Consump.	0.294	0.213	0.162	0.146	0.182
	Non-Energy Consump.	**0.015**	**0.010**	**0.008**	**0.004**	**0.007**
t-statistic	Gas Consump.	1.211	2.273	3.563	6.016	7.316
	Electricity Consump.	-0.931	1.184	1.714	3.861	3.909
	Non-Energy Consump.	-0.082	-2.279	-4.046	-10.583	-6.543
Uncompensated						
Coefficient	Gas Consump.	0.186	0.239	0.485	0.585	0.493
	Electricity Consump.	-0.325	0.107	0.092	0.468	0.561
	Non-Energy Consump.	**-0.995**	**-1.012**	**-1.019**	**-1.035**	**-1.035**
Robust Standard Errors	Gas Consump.	0.261	0.189	0.178	0.098	0.122
	Electricity Consump.	0.298	0.215	0.159	0.134	0.176
	Non-Energy Consump.	**0.015**	**0.010**	**0.008**	**0.003**	**0.008**
t-statistic	Gas Consump.	0.714	1.265	2.734	6.002	4.046
	Electricity Consump.	-1.091	0.497	0.581	3.499	3.179
	Non-Energy Consump.	**-65.698**	**-100.526**	**-134.900**	**-306.175**	**-135.861**
Number of obs		7,867.0	8,631.0	8,595.0	8,266.0	8,070.0
Log-likelihood		30937.805	38191.823	43161.867	44740.888	46895.141

Table 7: Price elasticities of demand, GB

[a] Own-price Elasticity Estimates in BOLD

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