Rebound effects for household energy services in the UK

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Abstract

This study estimates the combined direct and indirect rebound effects from energy efficiency improvements in the delivery of six energy services to UK households, namely: heating; lighting; cooking; refrigeration and clothes washing; entertainment and computing; and travel. We estimate a two-stage almost ideal demand system for household expenditure, with these energy services as expenditure categories. We estimate rebound effects in terms of carbon emissions and only include the 'direct' emissions associated with energy consumption. Our results suggest direct rebound effects of 70% for heating, 54% for travel and ~90% for the other energy services. But these effects are offset by negative indirect rebound effects. As a result, our estimates of combined rebound effects are smaller, namely 54% for heating, 67% for travel and ~40% for the other energy services. We also find some evidence that rebound effects have declined over time. We provide several caveats to these results, and indicate priorities for future research.

Keywords: *rebound effects; linear almost ideal demand system; energy efficiency*

1 Introduction

Major investments in energy efficient technologies are central to tackling climate change and a key source of green growth. Indeed, attempts to decouple energy services from energy use are crucial given the continually rising demand for energy. But to assess the effects of these investments on energy demand, it is important to understand the nature and magnitude of any associated 'rebound effects'.

The term 'rebound effects' refers to a variety of economic responses to improved energy efficiency whose net result is to increase energy consumption and greenhouse gas (GHG) emissions relative to a counterfactual baseline in which those responses do not occur. For example, more energy efficient lighting reduces the effective price of lighting which encourages consumers to use higher levels of illumination over longer periods of time, thereby offsetting some of the potential energy and emission savings. The magnitude of these effects has been a source of controversy for years, but an increasing volume of research has reduced some of the key uncertainties (Dimitropoulos et al., 2016; Sorrell, 2007; Turner, 2013). However, for energy efficiency improvements by consumers, the evidence base has three important limitations (Chitnis and Sorrell, 2015).

First, the majority of studies focus upon car travel, since reliable data on the effective price and quantity demanded of other household energy services is much harder to obtain (Galvin, 2015; Sorrell, 2007). Studies of rebound effects for lighting, for example, remain relatively rare (Saunders and Tsao, 2012; Tsao et al., 2010).

Second, most studies focus solely upon *direct* rebound effects and neglect the associated *indirect* rebound effects. For example, fuel-efficient cars may encourage more driving (direct rebound), but the savings on road fuels may be spent on other goods and services whose provision also requires energy use and emissions along their global supply chains (indirect rebound) (Chitnis et al., 2013; Druckman et al., 2011). From a global perspective, these emissions may further offset the environmental benefits of the energy efficiency improvements.

Third, most of the studies that estimate indirect rebound focus on the *income* effects of energy efficiency improvements and neglect the associated *substitution* effects - or in other words, they rely upon expenditure rather than price elasticities (Alfredsson, 2004; Bjelle et al., 2018; Murray, 2013; Thomas and Azevedo, 2013). As a result, their estimates of rebound effects are incomplete and likely to be biased (Chitnis and Sorrell, 2015).

To overcome these limitations, it is necessary to obtain estimates of both the own-price elasticity of demand for the relevant energy service (e.g. the own-price elasticity of lighting) and the elasticity of demand for other goods and services with respect to the price of that energy service (e.g. the elasticity of demand for food products with respect to the price of lighting). This can be achieved through estimating a system of equations for household expenditure on different categories of goods and services (a household demand model), where one of the categories is the relevant energy service. For example, to estimate the direct and indirect rebound effects associated with lighting, the model would need to include lighting as one of the categories of household expenditure, alongside other categories such as food and housing. This requires time-series, panel or pooled cross-sectional data on the price and expenditure share of each category of good and service, including the energy service (Chitnis and Sorrell, 2015; Sorrell, 2010). The price and expenditure share of lighting will, in turn, depend upon both the price of electricity and the average energy efficiency of the installed stock of light bulbs. Improvements in lighting efficiency will make lighting cheaper, thereby encouraging increased consumption of lighting along with increased (reduced) consumption of goods and services that are complements (substitutes) to lighting.

To convert these elasticity estimates into estimates of rebound effects, it is further necessary to estimate the energy use or emissions associated with household expenditure on each category of goods and service. For energy services such as lighting, these primarily derive from the *direct* energy use and emissions associated with household consumption of the relevant energy commodities - such as gas and electricity.[1] For other goods and services such as food and furniture, these primarily derive from the *embodied* energy use and emissions associated with manufacturing, processing, shipping and retailing those goods and services. Embodied energy use and emissions can be estimated with the help of multi-regional, environmentally-extended input output models (Breusch and Pagan, 1979; Chitnis and Sorrell, 2015; Chitnis et al., 2014; Chitnis et al., 2013; Druckman et al., 2011).

To date, as far as we know, no study has used this approach to estimate the *combined* (i.e. direct plus indirect) rebound effects for household energy services - owing primarily to a lack of data on the effective price of those services and their share of total household expenditure. However, several studies have estimated combined rebound effects for the energy commodities used to provide those energy services. For example, the combined rebound effect associated with household gas consumption has been estimated by combining estimates of the own- and cross-price elasticities of demand for natural gas with estimates of the energy or emission intensity of different categories of household expenditure. But this approach has two drawbacks. First, using energy commodity price elasticities as a proxy for energy service price elasticities will lead to biased estimates of the rebound effect (Chitnis and Sorrell, 2015; Sorrell, 2010). Second, additional bias will be introduced if the relevant energy commodity provides more than one energy services (e.g. electricity provides both lighting and entertainment), and/or the same energy service is provided by more than one energy commodity (e.g. heating is provided by both gas and oil) (Chan and Gillingham, 2015).

An earlier study by the authors (Chitnis and Sorrell, 2015) used the own and cross price elasticities of energy commodities to estimate combined rebound effects for UK households over the period 1964-2013. This gave estimates of 41% for measures affecting gas consumption, 48% for measures affecting electricity consumption and 78% for measures affecting vehicle fuels. This paper seeks to improve upon Chitnis and Sorrell (2015) in two ways. First, we estimate elasticities with respect to the

[1] The emissions associated with electricity consumption are normally classified as direct emissions, even though they occur at the generating plant rather than the household.

price of energy services rather than the price of energy commodities, thereby allowing individual energy services to be isolated and reducing one source of bias. Second, we distinguish between six categories of energy service, namely: i) space and water heating; ii) lighting; iii) cooking; iv) refrigeration and clothes washing; v) entertainment and computing; and vi) travel. This approach is made possible by a unique database on the consumption and price of those services in the UK over the last 51 years (Fouquet, 2008; Fouquet and Pearson, 2006).

This paper also differs from Chitnis and Sorrell (2015) in two other ways. First, to avoid the complications caused by different atmospheric lifetimes and radiative forcings, we estimate rebound effects solely in terms of carbon emissions rather than GHG emissions. In practice this makes little difference to the results, since carbon emissions dominate overall GHG emissions. Second, we confine attention to the *direct* emissions associated with the consumption of energy commodities and hence ignore the *embodied* (i.e. supply chain) emissions associated with the consumption of these and other goods and services (e.g. those associated with manufacturing and distributing clothes and furniture). This means we *ignore* the indirect rebound effects associated with increased/reduced consumption of non-energy goods and services (e.g. spending the cost savings from more efficient lighting on new clothes), but we *include* the indirect rebound effects associated with increased/reduced consumption of other energy services (e.g. spending the cost savings from more efficient lighting on more heating). One reason for adopting this simplified approach is that our earlier results suggested that own- and cross-price effects between different energy commodities (i.e. changes in direct emissions), accounted for the majority (i.e. >80%) of the combined rebound effect - implying that the neglect of embodied emissions should not lead to large errors. A second reason is that the limited degrees of freedom in our model greatly constrains the number of categories of goods and services that we can include - so we prioritise accurate estimates of the cross-price elasticities between different energy services rather than between those energy services and other commodity groups.

The following section summarises how we use estimates of the own- and cross-price elasticities and emission intensities of different goods and services to derive estimates of the combined rebound effect for a particular energy service. Section 2 describes the economic model used to derive the elasticities while Section 3 summarises the econometric techniques employed. Section 4 summarises our data sources, including our estimates of the effective price and quantity demanded of different energy services in UK households since 1964. Section 5 presents our results including our estimates of own-price and cross-price elasticities for each energy service, together with the associated rebound effects. Section 6 concludes by highlighting the limitations of this approach and providing some suggestions for future research.

2 Analytical expression for the combined rebound effect

Let x represent total household expenditure on all goods and services (e.g. in £); q_i the quantity of good or service i purchased by households and p_i the unit price of good i. We define a total of $N+1$ categories of goods and services ($i = 1,...N$, plus the energy service s), and allow these 'other' goods and services (i) to include both traded goods (e.g. furniture, clothes) and other energy services (heating, cooking). Total household expenditure may then be written as:

$$x = p_s q_s + \sum_{i=1,2...N} p_i q_i \qquad 1$$

Let R_{D_s} represent the direct rebound effect following a marginal improvement in the energy efficiency of delivering energy service s and let R_{I_s} represent the associated indirect rebound effect. The combined rebound effect for energy service s (R_{C_s}) is given by the sum of the two: $R_{C_s} = R_{D_s} + R_{I_s}$. With these definitions, Annex 1 derives the following expression for the combined rebound effect:

$$R_{C_s} = -\eta_{q_s,p_s} - \sum_{i(i\neq s)} \psi_i \eta_{q_i,p_s} \qquad 2$$

Where η_{q_s,p_s} is the own-price elasticity of demand for energy service s, η_{q_i,p_s} is the elasticity of demand for good i with respect to the price of energy service s and ψ_i is the ratio of the carbon emissions associated with expenditure on good i to the carbon emissions associated with expenditure on energy service s:

$$\psi_i = \frac{u_i w_i}{u_s w_s} \qquad 3$$

Where w_i is the share of category i in total household expenditure ($w_i = (p_i q_i)/x$), u_i is the carbon emission intensity of that expenditure (tCO_2/£) and w_s and u_s are the corresponding variables for energy service s. The emission intensities (u_i and u_s) may include both direct and embodied emissions, but in what follows we focus solely upon direct emissions.

The first term in Equation 2 is the direct rebound effect for energy service s (R_{D_s}):

$$R_{D_s} = -\eta_{q_s, p_s} \qquad 4$$

Equation 8 indicates that for there to be no direct rebound effect, the own-price elasticity of energy service consumption would need to be zero ($\eta_{q_s, p_s} = 0$).

The second term in Equation 2 is the indirect rebound effect for energy service s (R_{I_s}):

$$R_{I_s} = -\sum_{i(i \neq s)} \psi_i \eta_{q_i, p_s} \qquad 5$$

The total indirect rebound effect for energy service s (R_{I_s}) is the sum of the indirect rebound effects associated with each of the individual goods and services (i). The latter depend upon the elasticity of demand for the relevant good or service with respect to the effective price of the energy service (η_{q_i, p_s}) and the emissions associated with expenditure on that good or service ($u_i w_i$) relative to those associated with expenditure on energy service s ($u_s w_s$). Equation 5 demonstrates that goods and services with a small cross-price elasticity may nevertheless contribute a large indirect rebound effect if they are relatively emission intensive and/or have a large expenditure share (and vice versa). However, in what follows *we focus solely upon direct emissions, which means that the only goods and* *services contributing to our estimates of the indirect rebound effect are other energy services.* For example, improvements in heating efficiency may lead to indirect rebound effects associated with increased demand for lighting.

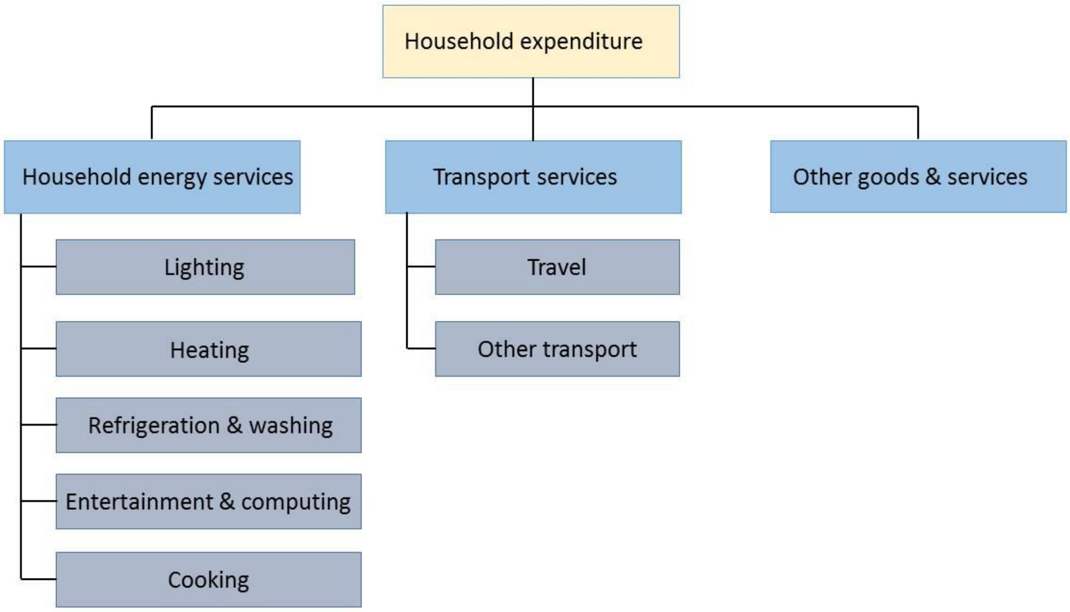
Note that the magnitude of the direct rebound effect is independent of the energy or emissions intensity of energy service *s,* and therefore independent of the metric used to measure rebound effects (e.g. energy, carbon or GHGs). In contrast, the magnitude of the indirect rebound effect depends upon the energy/emissions intensity of the energy service relative to other goods and services and hence depends upon the metric used.

3 Econometric model

Estimates of the required elasticities can be obtained by estimating a household demand model. One standard approach is to divide expenditures into a limited number of *aggregate categories* ($r=1...R$), and then to subdivide expenditure on each category into a number of *subcategories* ($i=1,...I^r$) - with the number of subcategories (I^r) varying from one aggregate category (r) to another. For example, the aggregate category of food products could be separated into 'animal products', 'vegetables and fruit' and 'other'. This approach assumes *weak separability* of preferences between aggregate commodity groups, such as food and transport - implying that household decisions on how much to spend on one group (e.g. food) are separate from decisions on how to allocate this expenditure between the goods and services within that group (e.g. animal products, vegetables and fruit) (Deaton and Muellbaeur, 1980). Although standard, this assumption can be a source of bias.

We follow the majority of studies in household demand analysis in using the *Linear Approximation to the Almost Ideal Demand System* (*LAIDS*), since this has a number of advantages over competing approaches (Deaton and Muellbauer, 1980). As a compromise between resolution and degrees of freedom, we split household expenditure into three categories and assume weak separability to give a two-stage budgeting framework (Figure 1). We assume households first allocate expenditure between three aggregate categories (household energy services, transport services, and other goods and services), and then distribute the expenditures on each of these aggregate categories (r) between individual subcategories (i). For this study we define six subcategories of household energy services, and two subcategories of transport services, but we do not disaggregate the aggregate category of other goods and services. This framework allows expenditure on individual subcategories to be specified as a function of the expenditure on the relevant aggregate category and the price of the subcategory.

Figure 1 Two-stage budgeting model



This framework includes a total of *six* energy services: namely, the five household energy services plus travel by private cars, motorbikes and vans. In each case, the relevant expenditures relate to the 'energy cost' of the energy service ($x_s = p_s q_s$) and exclude the associated capital and non-energy operating costs. For travel, the latter costs form part of the 'other transport' subcategory, which also includes expenditures on public transport. For household energy services, the capital and non-energy operating costs associated with the relevant equipment are included within the 'other goods and services' category.

The econometric model is specified as follows. Let x_t^r represent the expenditure on aggregate category r in period t and w_t^r the share of that category in total household expenditure (x_t):

$$w_t^r = \frac{x_t^r}{x_t} \qquad 6$$

In the first stage of the LAIDS model, this is specified as:

$$\mathrm{w_t^r} = \alpha^{\mathrm{r}} + \theta^{\mathrm{r}}\mathrm{t} + \sum_{\mathrm{s}=1,\ldots,\mathrm{R}} \gamma^{\mathrm{rs}}\ln \mathrm{p_t^s} + \beta^{\mathrm{r}}\ln\left(\frac{\mathrm{x_t}}{\mathrm{P_t^L}}\right) + \sum_{\mathrm{s}=1,\ldots,(\mathrm{R}-1)} \lambda^{\mathrm{rs}}\mathrm{w_{t-1}^s} + \nu_{\mathrm{t}}^{\mathrm{r}} \qquad 7$$

Where: r and s index over the aggregate categories (R=3); t is a time trend, p_t^s is the price of the aggregate category s in period t; x_t is total expenditure per household in that period; $\mathrm{P_t^L}$ is a log-linear analogue of the Laspeyres price index for household goods and services; w_{t-1}^s is the lagged expenditure share of category s; α^r, θ^{r}, γ^{rs}, β^r and λ^{rs} are the unknown parameters and $\nu_{\mathrm{t}}^{\mathrm{r}}$ is the error term. [2]

Our model departs from typical applications of LAIDS by using a loglinear analogue of the Laspeyres price index instead of standard Stone's price index ($\mathrm{P_t}$). $\mathrm{P_t}$ is defined as the expenditure-share weighted sum of the prices for the individual aggregate categories where the weight varies over time:

$$ln(P_t) = \sum_{r=1,\ldots,R} w_t^r ln(p_t^r) \qquad 8$$

Moschini (1995) shows that $\mathrm{P_t}$ is not invariant to changes in the units of measurement for prices and quantities, which may seriously affect the approximation properties of the model. Moschini (1995) suggests log-linear analogue of the Paasche price index ($\mathrm{P_t^P}$) and log-linear analogue of the Laspeyres price index ($\mathrm{P_t^L}$) as possible solutions: [3]

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[2] We also added a measure of heating degree days (to capture weather-related influences on energy demand) in both stages of estimation. This variable was generally insignificant and only had a minor effect on the size of estimated rebound. Hence, given the limited number of observations, it was dropped from the model.

[3] Moschini (1995) performed a simulation to illustrate the type of problems that may arise with the use of the Stone index. The linear AIDS with the standard Stone index, P, performed rather poorly. Indices $\mathrm{P_t^P}$ and $\mathrm{P_t^L}$ vastly improved the model with similar estimates, producing virtually the same results as the true non-linear AIDS model.

$$ln(P_t^P) = \sum_{r=1,\dots,R} w_t^r ln(\frac{p_t^r}{p_0^r}) \qquad 9$$

$$ln(P_t^L) = \sum_{r=1,\dots,R} w_0^r ln(p_t^r) \qquad 10$$

When the prices are expressed as indices, Equations 8 and 9 should be equivalent. However, since the expenditure share (w_t^r) in both equations is endogenous, the use of these price indices could result in biased estimates of Equation 7. We therefore use a log-linear analogue of the Laspeyres price index to overcome the endogeneity problem. In this index, (P_t^L), expenditure shares are held constant at their base year values (*t*=0).

We also include lagged expenditure shares (w_{t-1}^s) to the model. These have been found reduce serial correlation, while also capturing the inertia in price responses - for example as a result of the time taken to adjust spending habits to changes in prices (Edgerton, 1997; Klonaris and Hallam, 2003; Ryan and Plourde, 2009; Shukur, 2002). Since the lagged expenditure shares sum to unity, we drop one in each equation to avoid multi-collinearity. We also include a time trend (*t*) to capture the effect of time-varying factors influencing demand - an addition that we found to reduce serial correlation.

As with most applications of LAIDS, we impose restrictions on the parameter values to ensure the results are compatible with consumer demand theory. Specifically, *adding up* requires that expenditures on each category add up to total expenditure; *homogeneity* requires that the quantity demanded remains unchanged if prices and total expenditure change by an equal proportion; and *symmetry* requires that the Slustky matrix is symmetric.[4] These restrictions are implemented as follows:

Adding up: $\sum_{r=1..R} \alpha^r = 1$; $\sum_{r=1..R} \beta^r = 0$; $\sum_{r=1..R} \gamma^{rs} = 0$ *s=1,.R*; $\sum_{r=1..R} \lambda^{rs} = 0$ *s=1,.(R-1)*; and $\sum_{r=1,..R} \theta^r = 0$

[4] In other words, the compensated impact on the quantity demanded of category *r* of a unit increase in the price of category *s* should equal the compensated impact on the quantity demanded of category *s* of a unit increase in the price of category *r*. This condition halves the number of independent terms in the matrix.

Homogeneity: $\sum_{r=1..R} \gamma^{rs} = 0 \;\; s=1,..R$; Symmetry: $\gamma^{rs} = \gamma^{sr}$

The second stage of the LAIDS model distributes the category expenditures (x_t^r) between sub-categories. Let x_{it}^r represent expenditure on subcategory *i* in aggregate category *r* during period *t* ($i \in r$) and w_{it}^r represent the share of that subcategory in the expenditure on category *r* (x_t^r):

$$w_{it}^r = \frac{x_{it}^r}{x_t^r} \qquad 11$$

This is specified as:

$$w_{it}^r = \alpha_i^r + \theta_i^r t + \sum_{j=1,\ldots,k^r} \gamma_{ij}^r \ln p_{it}^r + \beta_i^r \ln\left(\frac{x_t^r}{P^{L}{}_t^r}\right) + \sum_{j=1,\ldots,(k^r-1)} \lambda_{ij}^r w_{jt-1}^r + \nu_{it}^r \qquad 12$$

Where *i* and *j* index over the subcategories within aggregate category *r* ($i, j \in r$); k^r is the number of subcategories in aggregate category *r* (i.e. five for household energy services, two for transport services); p_{it}^r is the price of subcategory *i* in aggregate category *r* in period *t;* x_t^r is the expenditure on category *r* period *t*; $P^{L}{}_t^r$ is the log-linear analogue of the Laspeyres price index for category *r*; α_i^r, θ_i^r, γ_{ij}^r β_i^r and λ_{ij}^r are the unknown parameters and ν_{it}^r is the error term. The price index for category *r* is defined as follows:

$$ln(P^{L}{}_t^r) = \sum_{i=1,\ldots,k^r} w_{i0}^r ln(p_{it}^r) \qquad 13$$

Again, the adding up, symmetry and homogeneity restrictions are imposed.

To estimate the expenditure and price elasticities for each category, we utilise the expressions derived for a two-stage budgeting model by Edgerton (1997). With this approach, 'total' elasticities are calculated from estimates of the 'between-category' and 'within-category' elasticities.[5] The relevant

[5] For interpretation of these elasticities see Chitnis and Sorrell (2015).

formulae are summarised in Table 1. Note that δ_{rs}, kronecker delta, is equal to unity when r=s (i.e. own-price elasticity) and zero otherwise, and δ^r_{ij} is equal to unity when i=j and zero otherwise.

Table 1 Analytical expressions for the between-category, within-category and total elasticities within a two-stage LAIDS model

Elasticity	**Expenditure**	**Price**
Between-category ($i \in r; j \in s; r \neq s$)	$\eta_{q_r,x} = 1 + \frac{\beta^r}{w^r}$	$\eta_{q_r,p_s} = \frac{\gamma^{rs} - \beta^r w_s}{w_r} - \delta_{rs}$
Within-category ($i, j \in r$)	$\eta^r_{q_i,x_r} = 1 + \frac{\beta^r_i}{w^r_i}$	$\eta^r_{q_i,p_j} = \frac{\gamma^r_{ij} - \beta^r_i w^r_j}{w^r_i} - \delta^r_{ij}$
Total	$\eta_{q_i,x} = \eta^r_{q_i,x_r}\eta_{q_r,x}$	$\eta_{q_i,p_j} = \delta_{rs}\eta^r_{q_i,p_j} + \eta^r_{q_i,x_r}(\delta_{rs} + \eta_{q_r,p_s})w^s_j$

Source: Edgerton (1997)

Note that when subcategories i and j are in different aggregate categories ($r \neq s$), $\delta_{rs} = 0$ and the expression for the total price elasticity reduces to:

$$\eta_{q_i,p_j} = \eta^r_{q_i,x_r}\eta_{q_r,p_s}w^s_j \qquad 14$$

When i and j are in the same category (r=s), the total price elasticity becomes:

$$\eta_{q_i,p_j} = \eta^r_{q_i,p_j} + \eta^r_{q_i,x_r}(1 + \eta_{q_r,p_r})w^r_j \qquad 15$$

We estimate these elasticities using the mean expenditure shares of each subcategory over the whole period. Finally, we use the total elasticities for each energy service (η_{q_s,p_s} and η_{q_i,p_s}) to estimate the direct and indirect rebound effects for that energy service (Equation 2).

4 Data

4.1 Expenditures and carbon intensities

Data on prices[6] and household expenditures for transport and other goods and services is taken from *Consumer Trends* published by the UK Office of National Statistics (ONS).[7] Data on the consumption and price of other energy services is taken from a variety of sources, as discussed below.[8] All data series are annual over the period 1964 to 2015. Note that, with our definitions, the total expenditure on household energy services is the same as the total expenditure on household energy commodities (e.g. heating oil, gas, electricity) while the expenditure on travel is the same as the expenditure on vehicle fuels (petrol and diesel). Since the composition of UK households has changed considerably over this period, we 'equivalise' total expenditure in each (sub) category as follows:

$$x_t = \frac{\bar{x}_t}{1 + 0.5a_t + 0.3c_t} \quad , \quad x_t^r = \frac{\bar{x}_t^r}{1 + 0.5a_t + 0.3c_t} \qquad 16$$

Where x_t and x_t^r are the equivalised expenditure of UK households on all categories and main category *r* respectively; $\bar{x}_t$ and $\bar{x}_t^r$ are the unadjusted expenditure on that category; a_t is the number of people over the age of 14 and c_t is the number of children below the age of 14. We take data on UK population size and composition from ONS.

We take data on the carbon intensities (tCO_2/kWh) of fuels from BEIS (2016a), and construct the carbon intensity of electricity from data on the share of different fuels in total electricity generation.[9] Combining data on the fuel mix for each energy service (see section 4.2.1) with data on household expenditure on each service, we construct the carbon intensity of expenditure on each service (u_s). For

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[6] Implied deflators (2012=100) are used for prices.

[7] www.ons.gov.uk

[8] For the purpose of estimation and consistency with non-energy services categories, we have used implied deflators (2012=100) from ONS to re-construct prices for energy services categories.

[9] Data for fuel mix and generation are taken from: www.gov.uk/government/statistical-data-sets/historical-electricity-data-1920-to-2011

consistency with expenditure shares, we use the mean of the carbon intensities over the whole time period.

4.2 Energy services

It is useful to consider energy services such as heating and car travel as being provided by a combination of energy *conversion devices* which transform energy from one form to another, and *passive systems* which hold or trap energy for a period of time (Cullen and Allwood, 2010; Cullen et al., 2011). For example, a boiler converts chemical energy into heat energy and a building traps heat energy for a period of time to deliver the energy service of heating. Similarly, an engine converts chemical energy into mechanical energy, and an (aerodynamic) car holds momentum for a period of time to deliver the energy service of travel. In what follows, we use the term *energy system*, to refer to the combination of conversion device and passive system that together deliver a particular energy service. We define the energy efficiency (ε) of this system as the ratio of energy service delivered (q_s) to energy consumed (q_e): $\varepsilon = q_s / q_e$. This in turn depends upon both the efficiency of the conversion device in converting energy, and the efficiency of the passive system in holding energy.

In any population of households, energy services such as heating may be supplied by more than one energy commodity (e.g. gas and electricity) and by more than one type of energy system (e.g. boilers, storage heaters). The average efficiency of the relevant energy systems will vary from one energy commodity to another (e.g. coal versus gas boilers) and will also change over time. Similarly, the quantity of energy services supplied by different energy commodities and/or energy systems will also change over time (e.g. shifts from coal to gas for heating, or from compact fluorescents to LEDs for lighting).

Fouquet (2008, 2014a) has constructed a database that includes annual estimates ($t=1,..T$) of the quantity consumed of each of E types of energy commodity ($e=1,..E$) within each of D types of energy system ($d=1,..D$) to produce each of S types of energy service ($s=1,..S$) within the population of UK households. We designate these estimates by ϕ_{sedt}. This dataset also includes estimates of the energy efficiency of each system/commodity combination (ε_{sedt}) together with the unit price of the relevant energy commodities (p_{et}). The quantity of energy service *s* produced by commodity *e* and system *d* in year *t* is then given by:

$$q_{sedt} = \phi_{sedt}\varepsilon_{sedt} \qquad 17$$

Similarly, the 'effective price' of that energy service is given by:

$$p_{sedt} = p_{et} / \varepsilon_{sedt} \qquad 18$$

The 'total cost' of the energy service also include the non-energy operating costs and discounted capital costs, but these are included in the 'other transport' category for travel and in the 'other goods and services' category for household energy services.

The total quantity of energy service *s* consumed in year *t* (q_{st}) is then given by summing over the relevant system/commodity combinations:

$$q_{st} = \sum_{e=1,..E} \sum_{d=1,..D} q_{sedt} \qquad 19$$

While the effective price of energy service *s* in year *t* is given by the weighted average of the effective price of the energy service from each system/commodity combination:

$$p_{st} = \sum_{e=1,..E} \sum_{d=1,..D} \left(\frac{q_{sedt}}{q_{st}} \right) p_{sedt} \qquad 20$$

For simplicity, we drop the time subscript in what follows, and represent the quantity demanded of energy service *s* by q_s and the effective price by p_s. We use the following measures for the quantity consumed (q_s) of each energy service:

- *travel*: vehicle kilometres;
- *space and water heating*: kWh heat

- *cooking*: kWh heat
- *lighting*: lumen-hours
- *washing*: kg of washed clothes
- *refrigeration*: litres of refrigerated space
- *entertainment:* kWh of effective appliance activity
- *computing:* kWh of effective computing.

4.2.1 Data sources for energy services

Our starting point in constructing time series for energy services is BEIS (2016b), which provides estimates of UK household energy consumption for each of five end-use categories (space heating, water heating, cooking, lighting and appliances), broken down by four types of energy commodity (coal, petroleum, natural gas and electricity), over the period 1970 to 2015. We obtain estimates for earlier years (1964 to 1970) using the process described in Fouquet (2014a) REMOVE "a" in (2014a). That is, it uses the energy commodity data available from past Digest of United Kingdom Energy Statistics and makes assumptions about the share of end-uses extrapolating back in time from 1970 and based on historical information about appliance markets – for the period from 1964 to 1970, the shares change little. BEIS (2016b) also provides estimates of electricity consumption for six end-use categories (lighting, cold appliances, wet appliances, consumer electronics, home computing and cooking) and breaks down each of these into individual energy systems (Table 2). We aggregate and combine this data to obtain estimates of energy consumption by commodity type (*e*) and energy system (*d*) for our five categories of household energy service (*s*), namely lighting, heating, refrigeration and washing, entertainment and computing, and cooking (ϕ_{sedt}).

Table 2 End-use categories and energy systems for electricity consumption

End-use category	**Energy system**

Lighting	Incandescent bulbs, halogen, fluorescent strip lighting, compact fluorescents, LEDs
Refrigeration	Chest freezer, fridge-freezer, refrigerators, upright freezers
Washing	Washing machines, washer-dryers, dishwashers and tumble dryers
Consumer electronics	TV, set top box, DVD/VCR, games consoles, power supply units
Home computing	desktops, laptops, monitors, printers and multi-function devices
Cooking	Electric ovens, electric hobs, microwaves and kettles for water heating

As described in Fouquet (2014a) REMOVE "a" in (2014a)., we use a variety of sources to obtain corresponding estimates of the energy efficiency of each system/commodity combination (ε_{sedt}). For example using and updating Fouquet (2014a) REMOVE "a" in (2014a)., we estimate that the energy efficiency of incandescent bulbs have increased from 11.7 lumens per watt (lm/W) 1964 to 15.2 lm/W in 2015. We obtain similar estimates for halogens, fluorescent strip lighting, compact fluorescents and LEDs, and use Equations 19 and 20 to estimate the total consumption and effective price of lighting in UK households since 1964.

We use a similar approach for other household energy services. In the case of refrigeration and washing, we use data from DCLG (2014) on the UK stock of refrigerators and washing machines (Table 2) at each energy rating band (i.e. A++, A+, A, B, D, E, F and G) in each year since 1996. Combining this with data on the energy efficiency of each band (Koomey et al., 2013), we estimate the weighted average energy efficiency of the UK stock of each appliance over the period 1996-2015. For earlier years, we incorporate less efficient label levels (H, I and J) and estimate the share of each using estimates of past diffusion rates (Fouquet, 2008).

For space heating, we use estimates from BEIS (2016b) on the efficiency of the residential energy system. The data is based on information from 1970 to 2015 on the Standard Assessment Procedure (SAP) rating, which measures the energy rating of residential dwellings, taking account of the typical building materials, level of insulation, rate of ventilation, and conversion efficiency of boilers. Using the observed correlation between heat loss and the date of construction of buildings (BEIS, 2016b), we estimate average heating efficiencies for the earlier period 1964 to 1969.

For entertainment and computing, we lack data on the share of different conversion devices by energy rating band. Instead, we base our trend estimates on the assumptions made by Brockway et al. (2014), which assumes a linear nine-fold increase in energy efficiency between 1970 and 2010, with the trend linearly extrapolated forward to 2015, but the rate of efficiency improvement prior to 1970 was only one quarter of the rate from the 1970s, reflecting the greater concern about efficiency. While highly simplistic, these estimates appear broadly consistent with the exponential improvements in the energy efficiency of computing technology reported by Koomey et al. (2013). They suggest that the energy efficiency of the combined category of entertainment and computing has improved twelve-fold between the 1960s and 2015. These efficiency estimates are then combined with the price of electricity to estimate the cost of entertainment and computing from 1964 and with the detailed break-down of consumption estimated in BEIS (2016b) back to 1970. Once estimates of consumption and prices for entertainment and computing are produced, and indexes are calculated for each, the indices are combined by weighting by the share of energy consumption for each service. This give a series for the price of entertainment and computing from 1964 to 2015 and the quantity consumed from 1970 to 2015. The latter is extrapolated back to 1964 using the 1970 share of entertainment in the total electricity use for appliances multiplied by the consumption of electricity for appliances - based on data from Fouquet (2014b) REMOVE “b” in (2014a)..

For transport services, we use DfT (2016) which provides data on passenger kilometres by car and motorcycle. The price of travelling one kilometre is estimated by dividing passenger expenditure by distance travelled (in billions of passenger kilometres). Passenger road transport costs are more complex when the consumer provides the transport service by driving a car or motorcycle. At least three costs can be identified: the fuel costs, other marginal costs and annualized costs. Fouquet (2012) breaks-down the annual costs of car travel between 1971 and 2008. Fuel costs accounted for between

28%-40% of the total annual expenses. Few of the other expenses listed are obvious marginal costs – tyre consumption also depends on distance travelled. So, fuel costs were used as the price (or main private marginal cost) of passenger transport. Fouquet (2012) provides further detail on the method for estimating the price of different transport services. The efficiency of travel is calculated by dividing distance travelled (vehicle-kilometre) by fuel consumption (MJ).

We emphasise that all the above estimates are subject to uncertainty - particularly for refrigeration and washing, and entertainment and computing. Improving the accuracy of these estimates should be a priority for future research.

4.2.2 Estimated trends

Here, we summarise our estimates of the effective price and consumption of each energy service in UK households since 1964. Figure 2 indicates the estimated trends in energy efficiency (ε_{st}) for each energy service between 1964 and 2015.[10] These represent the net effect of improvements in the efficiency of individual energy systems and changes in the mix of energy systems used for each energy service. For heating, average efficiencies (incorporating boiler efficiency and the thermal performance of the dwelling) improved more than three-fold between 1964 to 2015 (BEIS 2017) - a change driven by the shift from coal to gas heating in UK households and the increasing use of efficient, gas-fired condensing boilers. The efficiency of lighting improved steadily up to 2008 and then very rapidly following the penetration of CFLs and LEDs. We estimate the average efficiency of lighting to be ~39 lumens per watt (lm/W) in 2015 compared to only ~12 lm/W in 1964. The slight dip in lighting efficiency in 2014 and 2015 was due to a decrease in the share of relatively efficient fluorescent strips and a modest increase in less efficient halogen lighting.

We estimate that the efficiency of refrigeration and washing improved more than three-fold between 1964 and 2015, with most of this improvement occurring since 2000. The energy efficiency of travel

[10] Note that the axis for appliances is on the right-hand side of the figures.

increased by a more modest 55%, with technical improvements in energy efficiency being offset by the trend towards larger and more powerful vehicles (Ajanovic et al., 2012). Finally, we estimate that the energy efficiency of entertainment and computing increased by a factor of 12 over this period – although this estimate is uncertain.

Figure 2 Efficiency of providing household energy services in the UK 1964-2015 (1964=100)

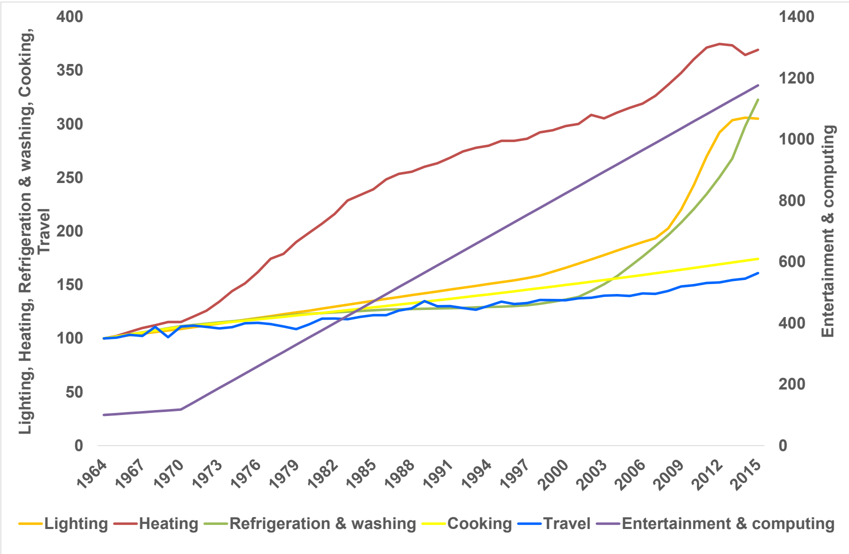
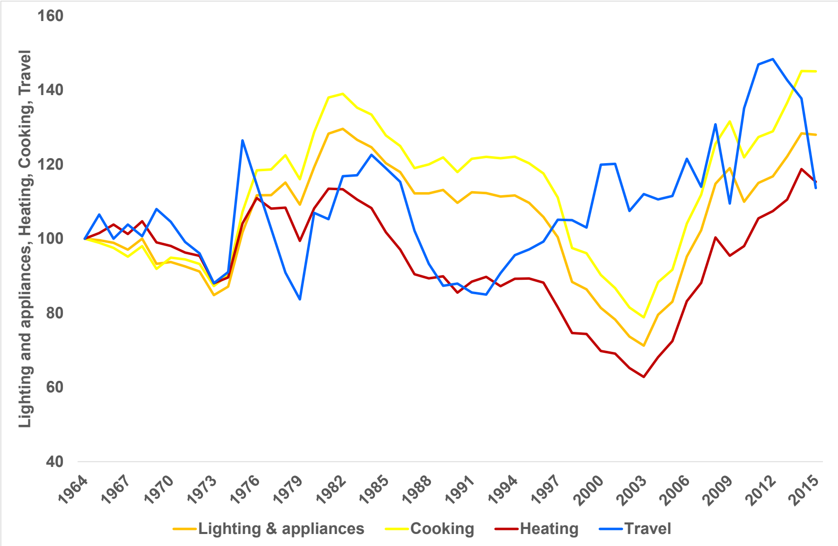


Figure 3 illustrates the estimated trends in the average 'energy input price' (p_{et}) for lighting and appliances, cooking, heating and travel respectively. For lighting and appliances the trend represents the unit price of electricity, while for cooking, heating and travel the trend represents the quantity-weighted average unit price of two or more energy commodities (Equation 20).[11] The trends reflect the net impact of changes in the real price of energy commodities and changes in the mix of energy commodities used for each category. The estimates suggest that energy input prices have fluctuated considerably over this period, with a steady decline between 1980 and 2004, significant increases to 2013 and a slight fall since that date. In real terms, the average energy input prices for lighting and appliances, heating and cooking are all estimated to be between 13% and 45% higher in 2015 compared to 1964, while the price of vehicle fuels is estimated to be around 13% higher (down from a peak of 48% in 2009).

[11] In all cases, standing and other charges are ignored.

Figure 3 Energy input real price for UK household energy services 1964-2015 (1964=100)



The real effective price of energy services (p_{st}) depends upon both average efficiencies (Figure 2) and energy input prices (Figure 3). The resulting trends are illustrated in Figure 4. Between 1980 and 2003, a combination of falling energy prices and improving efficiencies led to significant reductions in the effective price of household energy services. The real price of most energy services began to increase again after 2002, with a correlation in the price trends for lighting, cooking and refrigeration and washing - which are primarily provided by electricity. The effective price of travel began to rise after 1991 with the modest improvements in vehicle efficiency being insufficient to offset rising fuel prices. The most dramatic changes were in electronics and computing, with the effective price in 2015 being one fifth of that in 1964. In 2013, the real price of lighting was around 48% lower than in 1964, refrigeration and washing 23% lower, entertainment and computing 88% lower, cooking 17% lower and heating only 20% lower.

Figure 4 Real effective price of UK household energy services 1964-2015 (1964=100)

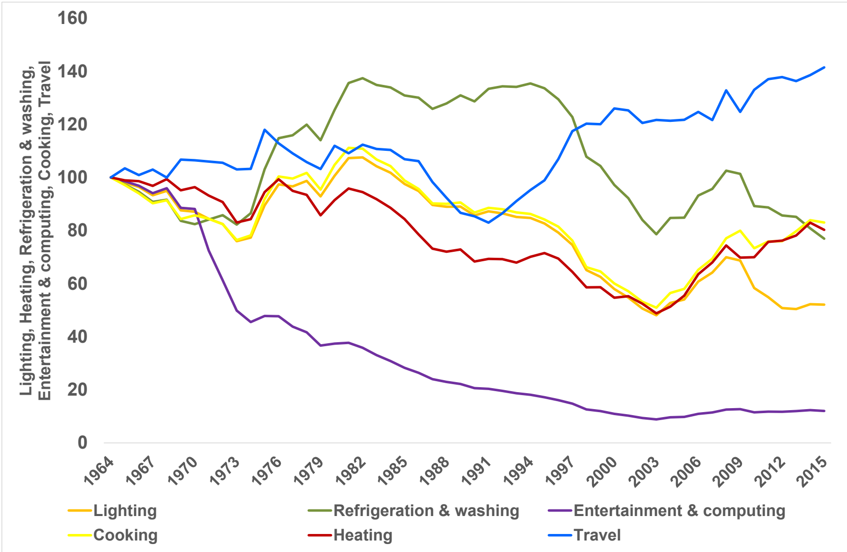
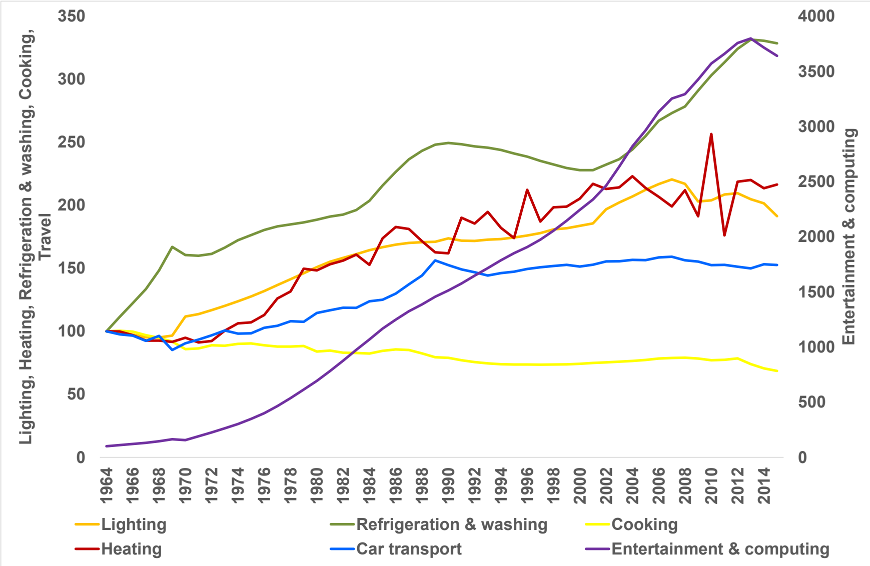


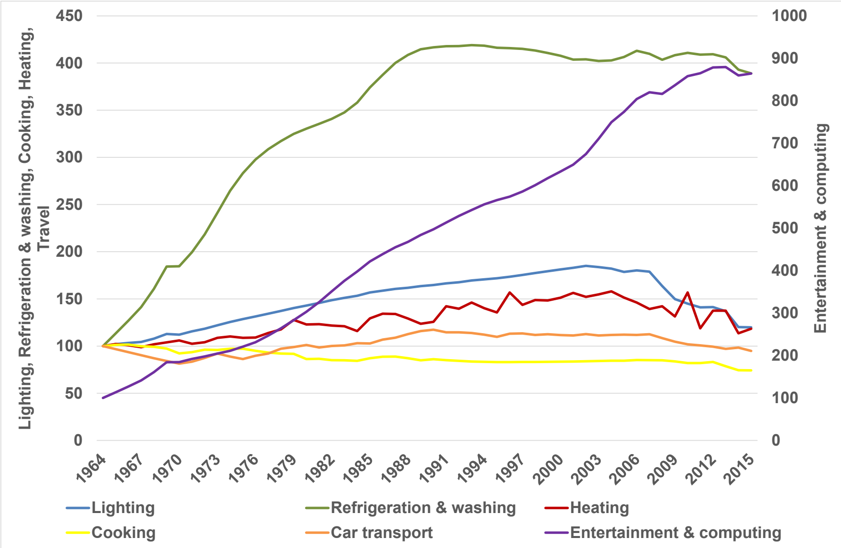
Figure 5 illustrates the resulting trends in household consumption of energy services over this period. Consumption of residential heating and lighting is estimated to have increased by a factor of four since the mid-1960s, while consumption of refrigeration and washing increased seven-fold and entertainment and computing 100-fold. In contrast, consumption of cooking is estimated to have increased only 30% - perhaps reflecting greater reliance upon ready-meals and eating out. Consumption of refrigeration and washing appears to have accelerated after 2000, while consumption of other services has stabilised or even begun to decline. The latter trend is particularly important for travel, where it has been labelled peak car'. Note that the annual variations in heating consumption are related to variations in average winter temperatures.

Figure 5 Consumption of UK household energy services 1964-2015 (1964=100)



Finally, Figure 6 illustrates the estimated trends in energy consumption for each service. Consumption of energy has not growing as fast as consumption of the energy services themselves, owing to the improvements in energy efficiency. For example, consumption of energy for heating was around 20% higher in 2015 and 1964, while consumption of heating services was around 100% higher. For cooking, improvements in efficiency have combined with reductions in cooking demand to lead to a ~60% reduction in energy consumption. For appliances, efficiency improvements have moderated but not offset the rise in service demand, with the result that energy consumption for refrigeration increased 220%, electricity use for washing rose by 365%, energy for electronics soared by 765% between 1964 and 2015, and that for computing increased by 110% between 2000 and 2015.

Figure 6 Consumption of energy for UK household energy services 1964-2015 (index)



5 Results

5.1 Elasticity estimates

Our two-stage budgeting model (Figure 1) leads to three equations for the aggregate groups, five equations for the household energy services group and two equations for the transport group. We impose the adding-up restriction by dropping one of the equations in each group.

Tables B.1 to B.3 in Annex B summarise the resulting parameter estimates for the aggregate groups, household energy services group and transport group respectively. To interpret the results we need to derive the elasticity estimates. Table C.1 and C.2 in Annex C summarise the *between-group* elasticity estimates while Table C.3 and C.4 summarise the *within-group* estimates – with the results from the household energy services and transport groups being combined within the same table. We insert these results into Equations in Table 1 to provide estimates of the *total expenditure* ($\eta_{q_i x}$) and *total price* ($\eta_{q_i p_j}$) elasticities for each of our six energy services - which are summarised in Table 3 and Table 4. We then insert the total price elasticity estimates into Equation 2 to derive estimates of the direct and indirect rebound effects for each of our six energy services. Table 5 indicates the resulting estimates of the indirect rebound effect between each energy service (for example, between heating and lighting). Finally Table 6 sums the estimates in Table 5 to give the overall direct, indirect and combined rebound effect for each energy service.

From Table 3 we observe that the estimated expenditure elasticities for the energy services are all greater than 0.86, and for both heating and refrigeration and washing they exceed unity. This contrasts with Chitnis and Sorrell (2015) who found relatively low expenditure elasticities for the energy commodities supplying those services. Efficiency improvements may partly explain this difference, but other factors are likely to have influenced the results. Very few studies have estimated expenditure elasticities for these energy services (either for the UK or for other countries), but we observe that our estimate of the expenditure elasticity of lighting is approximately twice that found by Fouquet (2014b) REMOVE "b" in (2014b).,[12] while our estimate of the expenditure elasticity of heating is approximately 40% larger.

The estimated own-price elasticities for the energy services are indicated in the main diagonal of Table 4 (in bold). These all have the expected sign but are larger than anticipated: namely, -0.7 for heating, -0.5 for travel and ~-0.9 for other energy services. Again, few studies provide comparable estimates of these elasticities, but we observe that our estimate of the own price elasticity of lighting is almost twice as large as that found by Fouquet (2014) , while our estimates of the own price elasticities of heating and travel are at the upper end of the range found in the literature (Galvin, 2015; Madlener and Hauertmann, 2011; Sorrell, 2007).

Table 4 also indicates the estimated cross-price elasticities between the six energy services. Looking first at the signs of the elasticities we observe that travel is estimated to be a complement to household energy services ($\eta_{q_i,p_s} < 0$), while the individual household energy services are estimated to be substitutes ($\eta_{q_i,p_s} > 0$). This suggests, for example, that improvements in the energy efficiency of lighting are associated with increased demand for travel but reduced demand for heating. The emissions associated with the former will amplify the rebound effect from energy efficient lighting,

[12] These estimates relate to the year 2000 and hence are prior to the rapid efficiency improvements of the last decade.

while those associated with the latter will offset it. It is difficult to judge whether the estimated signs are plausible or not, since there are no other studies with which we can compare.

Looking next at the estimated magnitude of these elasticities, we observe that most are relatively modest in size (i.e. <0.09) - which is what we would expect. The main exception is heating, where a 1% reduction in the effective price of heating (i.e. a 1% improvement in energy efficiency) is associated with a ~0.35% reduction in demand for other household energy services, but only a 0.03% increase in travel demand.

5.2 Rebound effects

Our estimates of the own price elasticities of each energy service translate directly into estimates of the direct rebound effect for those services (Table 5). The results suggest very large direct rebound effects, namely: 70% for heating, 54% for travel and >90% for the other energy services.[13] As noted, these are larger than the majority of estimates in the literature.

Table 5 also summarises the estimated indirect rebound effects between each pair of energy services (e.g. between heating and lighting), while Table 6 summarises the total indirect effect summing over all energy services, together with the total combined (i.e. direct plus indirect) rebound effect. Taking lighting as an example, the indirect rebound effects associated with other household energy services (e.g. heating) offset the direct rebound effect, while the indirect rebound effect associated with travel amplifies the direct rebound effect. Overall, the sum of individual effects over all energy services is significant (Table 6). For example, the total indirect rebound effect for lighting is estimated to be -54%. This offsets the estimated direct rebound effect of 94% for lighting to leave a combined rebound effect of 40%. Similar comments apply to the other household energy services. But for travel the direct and indirect rebound effects have the same sign, so the combined rebound effect is larger than

[13] We experimented two estimation methods/models: Ordinary Least Square (OLS) with Heteroskedastic and Autocorrelation Consistent (HAC) estimator for a model with no lagged budget shares, and Iterative Seemingly Unrelated Regressions (ISUR) for a model with lagged budget shares. Overall, our estimates of direct rebound appeared relatively insensitive to above choices.

the direct effect. Overall, we estimate a combined rebound effect of 40% for lighting, 54% for heating, 67% for travel and ~40% for the other energy services.

One notable feature of the results is the similarity of the estimated direct and indirect rebound effects for lighting, refrigeration and washing, and entertainment and computing. While each is provided by electricity, we would have expected the results to be different given the diverging trends in the effective price of each service (Figure 4). But given the similarity in the results, we re-estimated the model with these three expenditure categories combined. This led to *lower* estimates of the combined rebound effect for each of our energy service categories (Table 7): namely 30% for lighting and appliances, 50% for travel, 48% for heating and 27% for cooking. These lower estimates primarily derive from lower estimates of the direct rebound effect. This suggests that the results are sensitive to the level of aggregation used, which demonstrates the need for caution in interpretation.

We also estimated the combined rebound effects for each energy service in 1964 and 2015 (
Table 8) This was achieved by using the expenditure share of each good and service in those years, together with the corresponding carbon intensity of electricity consumption. The results suggest that the magnitude of the combined rebound effects have *fallen* over time. For example, the combined rebound for lighting is estimated to have fallen from 36% in 1964 to only 7% in 2015 while that for heating has fallen from 56% to 51%, and that for travel has fallen from 72% to 51%. The exception is cooking, where the combined rebound effect has increased from 20% to 25%.

Table 3 Total expenditure elasticity estimates ($\eta_{q_i,x}$)

Energy service	Total expenditure elasticity
Lighting	0.9618
Heating	1.2924
Refrigeration and washing	1.1036
Entertainment & computing	0.8607
Cooking	0.9748
Travel	0.8880

Table 4 Total price elasticity estimates (η_{q_i,p_j})

	Total price elasticity					
	Lighting	Heating	Refrigeration and washing	Entertainment & computing	Cooking	Travel
Lighting	**-0.9362**	0.3811	0.0880	0.0587	0.0361	-0.0375
Heating	0.0405	**-0.6960**	0.0650	0.0309	0.0435	-0.0504
Refrigeration & washing	0.0495	0.3432	**-0.9224**	0.0436	0.0492	-0.0430
Entertainment & computing	0.0554	0.3996	0.0897	**-0.9440**	0.0586	-0.0336
Cooking	0.0353	0.3696	0.0811	0.0468	**-0.9188**	-0.0380
Travel	-0.0036	-0.0264	-0.0058	-0.0033	-0.0038	**-0.5417**

Note: Each row represents an equation. So for example, a 1% increase in the price of lighting will lead to a 0.93% reduction in lighting consumption and a 0.04% increase in heating consumption.

Table 5 Estimated direct and indirect rebound effects for each energy service

	Lighting	Heating	Refrigeration & washing	Entertainment & computing	Cooking	Travel
Lighting	93.6%	-39.4%	-8.0%	-4.7%	-3.5%	1.8%
Heating	-3.9%	69.6%	-5.7%	-3.5%	-3.8%	1.4%
Refrigeration & washing	-5.5%	-39.3%	92.2%	-4.7%	-5.0%	1.8%
Entertainment & computing	-7.0%	-35.6%	-8.3%	94.4%	-5.5%	2.0%
Cooking	-3.6%	-42.7%	-8.0%	-5.0%	91.9%	2.0%
Travel	0.7%	9.7%	1.4%	0.6%	0.8%	54.2%

Table 6 Direct, indirect and combined rebound effects for each energy service

Energy service	**Direct rebound**	**Indirect rebound**	**Combined rebound**
Lighting	93.6%	-53.7%	39.9%
Heating	69.6%	-15.5%	54.1%
Refrigeration & washing	92.2%	-52.7%	39.5%
Entertainment & computing	94.4%	-54.3%	40.0%
Cooking	91.9%	-57.3%	34.6%
Travel	54.2%	13.1%	67.3%

Table 7 Direct, indirect and combined rebound effects for each energy service – lighting and appliances combined

Energy service	**Direct rebound**	**Indirect rebound**	**Combined rebound**
Lighting and appliances	84.8%	-54.8%	30.0%
Heating	63.6%	-15.7%	48.0%
Cooking	95.0%	-67.4%	27.6%
Travel	57.2%	-7.0%	50.2%

Table 8 Comparing estimates of the direct, indirect and combined rebound effects for each energy service in 1964 and 2015

Energy service	**1964**			**2015**		
	Direct rebound	Indirect rebound	Combined rebound	Direct rebound	Indirect rebound	Combined rebound
Lighting	94.0%	-48.0%	46.0%	93.7%	-86.2%	7.5%
Heating	68.5%	-12.2%	56.2%	64.9%	-13.8%	51.1%
Refrigeration & washing	95.8%	-59.3%	36.6%	90.0%	-82.4%	7.5%
Entertainment & computing	96.0%	-45.6%	50.4%	89.2%	-81.9%	7.3%
Cooking	89.7%	-69.5%	20.2%	91.4%	-66.9%	24.5%
Travel	44.2%	27.6%	71.8%	44.5%	6.1%	50.6%

6 Conclusion

This study has sought to estimate the combined direct and indirect rebound effects associated with improvements in the energy efficiency of UK household energy services over the period 1964 to 2015. These effects have been estimated solely in terms of the carbon emissions associated with energy consumption - the emissions 'embodied' in non-energy goods and services have been ignored. To our knowledge, this is the first study of its type to estimate both own and cross-price elasticities between different household energy services, as well as the first to use these to estimate rebound effects. The study improves upon earlier work by Chitnis and Sorrell (2015), since it does not rely on the assumption that the own-price elasticity of energy service demand is equal to the own-price elasticity of energy demand.

The approach relies upon a unique database on the price and consumption of household energy services in the UK since 1964. These estimates suggest that the effective price of most energy services have fallen significantly since 1964 (Figure 4), although rising energy prices over the last few years have partly offset the effect of improving efficiency. The only exception is vehicle travel, where the price per kilometre in 2015 was ~14% higher than in 1964.

The results suggest, first, that the direct rebound effects from energy efficiency improvements over this period have been relatively large – for example, 94% for lighting and 70% for heating. While few other studies have estimated these effects, our estimates are at the high end of the range found in the literature.

Second, our results suggest that the indirect rebound effects associated with other energy services are significant – namely +13% for travel, -16% for heating and -55% for other household energy services. These indirect effects *offset* the direct rebound effect for household energy services, but *amplify* the direct rebound effect for travel. This is because household energy services are estimated to be substitutes for each other, while travel is estimated to be a complement. The net result is that the combined rebound effect is smaller than the direct rebound effect for household energy services, but larger for travel. Overall, we estimate a combined rebound effect of 40% for lighting, 54% for heating, 67% for travel and ~40% for the other energy services. These results suggest that around one half of the potential emission savings from improved energy efficiency over this period have been 'taken back' by consumer responses to cheaper energy services.

There are multiple caveats to these results. First, our re-estimation of the model with aggregated categories of energy services leads to lower estimates of the combined rebound effect (

Table 7), suggesting that the results are sensitive to the level of aggregation used. This sensitivity may derive in part from the relatively small share of total expenditure accounted for by individual energy services. Second, there are considerable difficulties in compiling estimates of the effective price and quantity demanded of household energy services over this period - and particularly for years prior to 1970. The resulting uncertainties limit the level of confidence we can have in the results - especially for categories such as entertainment and computing where the quality of data is particularly poor. Third, the limited number of observations in our model prevents us from including additional covariates and necessitates the imposition of separability assumptions - both of which could potentially bias the results. Fourth, our estimates of expenditure elasticities are relatively large and notably larger than those found by Fouquet (2012) who used a comparable dataset. Fifth, some of our cross price elasticity estimates are puzzling, including the finding of substitutability between heating and lighting. Since energy efficient lighting produces less waste heat, we would expect an increase in heating consumption to compensate (the 'heat replacement effect'), but our results suggest the opposite. Finally, we note that our study neglects embodied emissions and hence the indirect rebound effects associated with changes in the consumption of non-energy goods and services. Although the sign of these effects is ambiguous and their magnitude is likely to be small, their inclusion would necessarily change our estimates of the total rebound effect.

Future work should seek to address some of these limitations and improve the level of confidence in the results. This is particularly important since other studies that have used a comparable methodology - only with energy commodities rather than energy services - have also estimated large rebound effects (Chitnis and Sorrell, 2015; Mizobuchi, 2008). For example, Brannlund *et al* (2016) estimated rebound effects in excess of 100%. At this stage, it is not clear whether these large estimates reflect a problem with this type of methodology (i.e. multistage household demand models), or whether they provide an accurate reflection of the size of rebound effects from household energy efficiency improvements. Nevertheless, the consistency of these results – and their potentially significant implications for climate policy - reinforces the need to investigate rebound effects more carefully.

Annex A – Rebound model

Assume a household makes a costless investment that increases the energy efficiency (ε_s) of providing energy service *s* by $\varsigma = \Delta\varepsilon_s / \varepsilon_s$ ($\varsigma \geq 0$), thereby reducing the energy cost (p_S) of that service by $\tau = \Delta p_S / p_S$ ($\tau \leq 0$). Let *Q* represent the household's baseline carbon emissions (direct plus embodied), ΔH the change in emissions that would occur *without* any behavioural responses to the lower cost energy service (the 'engineering effect'), ΔG the change in emissions that results from those behavioural responses (the 're-spending effect'), and $\Delta Q = \Delta H + \Delta G$ the net change in carbon emissions. The combined rebound effect (R_{C_s}) is then given by:

$$R_{C_s} = \frac{\Delta H - \Delta Q}{\Delta H} = -\frac{\Delta G}{\Delta H} \qquad 21$$

As discussed in Section 2, this is comprised of direct and indirect effects ($R_{C_s} = R_{D_s} + R_{I_s}$). The baseline carbon emissions for the household may be written as:

$$Q = x_s u_s^x + \sum_{i(i \neq s)} u_i x_i \qquad 22$$

Where x_i is the expenditure on commodity *i* (in £), u_i^x is the carbon intensity of that expenditure (in tCO_2/£) and x_S and u_s are the corresponding values of these variables for energy service *s*. The carbon intensities may include both direct and embodied emissions.

To estimate the engineering effect (ΔH), we assume the consumption of all commodities remains unchanged while the energy cost of the energy service falls. The change in expenditure on the energy service as a consequence of the engineering effect is then given by $\Delta x_S^H = q_S \Delta p_S$. Given that $\Delta p_s = \tau p_s$ and $\Delta H = u_S^x \Delta x_S^H$ we obtain the following expression for the engineering effect:

$$\Delta H = u_s x_s \tau \qquad 23$$

To estimate the re-spending effect (ΔG), we must allow for the change in expenditure on each commodity group (Δx_i).The change in expenditure on the energy service itself as a consequence of the engineering effect is given by $\Delta x_s^G = p_s \Delta q_s$.[14] Adding in the change of expenditure on other commodity groups we obtain the following expression for the re-spending effect:

$$\Delta G = u_s \Delta x_s^G + \sum_{i(i \neq s)} u_i \Delta x_i \qquad 24$$

Assuming marginal changes, we can use elasticities to substitute for Δx_s^G and Δx_i in this equation:

$$\Delta G = u_s x_s \tau(\eta_{x_s,p_s} - 1) + \sum_{i(i \neq s)} u_i x_i \tau \eta_{x_i,p_s} \qquad 25$$

Substituting the expressions for ΔH (Equation 23) and ΔG (Equation 25) into Equation 21 and noting that $w_i = x_i / x$, we arrive at the following expression for the combined rebound effect:

$$R_{C_s} = (1 - \eta_{x_s,p_s}) - \sum_{i(i \neq s)} \psi_i \eta_{x_i,p_s} \qquad 26$$

Where:

$$\psi_i = \frac{u_i w_i}{u_s w_s} \qquad 27$$

For ease of exposition, we typically express elasticities in quantity form. Given that $(1 - \eta_{x_s,p_s}) = -\eta_{q_s,p_s}$ and $\eta_{x_i,p_s} = \eta_{q_i,p_s}$, the combined rebound effect can also be written as:

$$R_{C_s} = -\eta_{q_s,p_s} - \sum_{i(i \neq s)} \psi_i \eta_{q_i,p_s} \qquad 28$$

The first term in Equation 28 is the direct rebound effect for energy service *s* (R_{D_s}) and the second is the indirect rebound effect (R_{I_s}). The first depends solely upon the own-price elasticity of energy service demand (η_{q_s,p_s}), while the second depends upon the elasticity of demand for commodity *i*

[14] For the energy service itself, the total change in expenditure is the sum of the engineering and re-spending effects: $\Delta x_s = \Delta x_s^H + \Delta x_s^G$

with respect to the energy service (η_{q_i,p_s}) and the carbon intensity and expenditure share of that commodity relative to that of the energy service (ψ_i).

Annex B – Parameter estimates

Table B.1 Parameter estimates from stage 1 - aggregate groups

	α^r	θ^r	β^r	γ^{rs}			λ^{rs}		$\overline{R}^2$
				Household energy services	Transport services	Other goods and services	Household energy services	Transport services	
Household energy services	**0.0176	***-0.0002	0.0055	***0.0166	-0.0057	***-0.0109	***0.5276	**0.0721	0.93
	(0.0069)	(0.0001)	(0.0057)	(0.0023)	(0.0034)	(0.0038)	(0.0761)	(0.0351)	
Transport services	-0.0059	***0.0004	**-0.0208	-0.0057	**0.0239	*-0.0182	0.1902	***0.8175	0.94
	(0.0129)	(0.0001)	(0.0107)	(0.0034)	(0.0099)	(0.0098)	(0.1343)	(0.0670)	
Other goods and services	0.9883	-0.0002	0.0153	-0.0109	0.0239	0.0291	-0.7178	0.8896	-

Notes:

- *Standard errors* in parenthesis. ***, ** and * indicate statistical significance at 1%, 5% and 10% probability levels respectively. $\overline{R}^2$ is the adjusted R^2.
- Coefficients for 'other goods & services' are estimated from the adding-up and homogeneity restrictions.
- The lagged budget share of 'other goods & services' is dropped to avoid co-linearity.

Table B.2 Parameter estimates from stage 2 – household energy services group

	α_i^r	θ^r	β_i^r	γ_{ij}^r					λ_{ij}^r				$\bar{R}^2$
				Lighting	Heating	Refrigeration and washing	Entertainment & computing	Cooking	Lighting	Heating	Refrigeration and washing	Entertainment & computing	
Lighting	***0.2643	***0.0018	***-0.0153	***0.0010	0.0000	***0.0004	0.0001	***-0.0014	-0.0230	***-0.3248	***-0.2203	***-0.9623	0.94
	(0.0963)	(0.0003)	(0.0060)	(0.0004)	(0.0002)	(0.0001)	(0.0001)	(0.0005)	(0.1897)	(0.0903)	(0.0860)	(0.1662)	
Heating	***-0.8697	***-.01089	***0.0598	0.0000	***0.0019	***-0.0005	***-0.0005	***-0.0008	*** 3.0646	***2.1054	***1.2415	***4.6474	0.93
	(0.3526)	(0.0012)	(0.0227)	(0.0002)	(0.0004)	(0.0002)	(0.0001)	(0.0002)	(0.6791)	(0.3353)	(0.3417)	(0.6346)	
Refrigeration and washing	***0.4870	***0.0036	-0.0085	***0.0004	***-0.0005	***0.0002	0.0001	-0.0001	***-1.2923	***-0.5085	***0.4328	***-1.7589	0.96
	(0.1478)	(0.0005)	(0.0093)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.2933)	(0.1403)	(0.1414)	(0.2558)	
Entertainment & computing	0.1512	***0.0036	***-0.0206	0.0001	***-0.0005	0.0001	***0.0004	-0.0000	**-0.4854	***-0.2564	***-0.4000	-0.02692	0.99
	(0.1125)	(0.0004)	(0.0073)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.2126)	(0.1036)	(0.1023)	(0.1930)	
Cooking	0.9672	0.0019	-0.0239	-0.0014	-0.0008	-0.0002	-0.0000	0.0024	-1.2639	-1.0157	-1.054	-1.9531	-

Notes:

- Coefficients for 'cooking' are estimated from the adding-up restriction.
- The lagged budget share of 'cooking' is dropped to avoid co-linearity.

Table B.3 Parameter estimates from stage 2 –transport group

	α_i^r	θ_i^r	β_i^r	γ_{ij}^r		λ_{ij}^r	$\overline{R}^2$
				Travel	Other transport	Travel	
Travel	***0.2390	-0.0006	0.0145	***0.0937	***-0.0937	***0.2569	0.73
	(0.0773)	(0.0004)	(0.0242)	(0.0116)	(0.0116)	(0.0693)	
Other transport	0.761	0.0006	-0.0144769	-0.0937	0.0937	-0.2569	-

Annex C – Between group and within group elasticity estimates

Table C.1 Between-group expenditure elasticity estimates ($\eta_{q_r x}$)

	Between-group expenditure elasticity
Household energy services	1.1781
Transport	0.8336
Other goods and services	1.0182

Table C.2 Between-group price elasticity estimates ($\eta_{q_r p_s}$)

	Between-group price elasticity		
	Household energy services	Transport	Other goods and services
Household energy services	-0.4664	-0.2071	-0.5045
Transport	-0.0402	-0.7881	-0.0052
Other goods and services	-0.0135	-0.0239	-0.9809

Table C.3 Within-group expenditure elasticity estimates ($\eta^r_{q_i, x_r}$)

	Within-group expenditure elasticity
Lighting	0.8164
Heating	1.0970
Refrigeration & washing	0.9368
Entertainment & computing	0.7306
Cooking	0.8275
Travel	1.0653

Table C.4 Within-group price elasticity estimates ($\eta^{r}_{q_i,p_j}$)

	Within-group price elasticity					
	Lighting	Heating	Refrigeration & washing	Entertainment & computing	Cooking	Travel
Lighting	-0.9724	0.1126	0.0292	0.0254	-0.0028	-
Heating	-0.0081	-1.0568	-0.0139	-0.0139	-0.0087	-
Refrigeration and washing	0.0080	0.0352	-0.9898	0.0053	0.0046	-
Entertainment & computing	0.0230	0.1593	0.0371	-0.9739	0.0238	-
Cooking	-0.0014	0.0975	0.0216	0.0130	-0.9582	-
Travel	-	-	-	-	-	-0.5917

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